Thesis

Towards Sustainable Dynamic Traffic Management

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adviseurs mobiliteit
Goudappel Coffeng

TOWARDS SUSTAINABLE DYNAMIC TRAFFIC MANAGEMENT

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Je gaat het pas zien als je het doorhebt

You can only see it, when you get it

Johan Cruijff

Prologue

"Good morning Luc, it is now 7.30 AM and your coffee is ready." It was a good idea, updating his preferences yesterday in his Personal Assistant Device (PADdy). Coffee for breakfast was more than enough today. Yesterday he had been working late with colleagues from all over the world to improve the open source software 'SchedPPT' that was used in different countries. PADdy continuous, "Your personalized public transport vehicle will be picking you up at 8.15 AM and your first meeting today will be a teleconference at 8.30 AM, while you are travelling to Amsterdam. Because no congestion problems are predicted your estimated arrival time will be 9.02 AM. Your meeting starts at 9.15 AM and after finishing your meeting at 10.30 AM you will travel to Enschede arriving at 11.05 AM."

Luc did not understand why PADdy was still talking about congestion problems, because those problems had not occurred since 2040. After the economic crisis and the even bigger energy crisis, traffic engineers from all over the world had been working even harder on developing systems for sustainable traffic and transport. Luc had also worked on this subject for many years and had finished his PhD research in 2012 about the deployment of dynamic traffic management (DTM) measures improving accessibility and reducing externalities. Till then, the focus was mainly on accessibility, because mobility was seen as a prequisite of economic growth. Even when externalities were considered, these were usually formulated as constraints rather than objectives. In addition, main practice was the optimization of these DTM measures on a local or corridor level. When a network approach was applied on strategic level, this approach was often based on an evaluation of a few predefined scenarios based on expert judgment. His research was one of the first steps towards sustainable traffic management that provided insights on how the various externalities interact and what strategies could be used to optimize them, taking traffic dynamics and the behavioral response of road users into account. After he had finished his research, developments had been going fast. The crises and new insights had led to a change of believe of policy makers that it could no longer suffice to focus on accessibility only. Because of the increasing data availability, understanding of behavior and developments in technology, complete system wide optimization procedures became possible in 2035, solving many of the traditional traffic and transport problems. Twente University and Goudappel Coffeng had played a significant role in this.

The introduction of personalized public transport using fuel cells had been a difficult process, but now it was embraced by society and no one owned a car anymore. Using your PADdy, it had become very easy to travel and to manage your agenda. Your PADdy automatically booked personalized public transport and incorporated, if necessary, travel times. A management system optimized handling all travel demand in such a way that everyone could arrive at his/her destination in time, while reducing the external effects. Unless, of course, you waited too long to book. Weighting the various objectives was still a public policy decision, which means that the selected best compromise solution depends on the elected government. In the Netherlands also SchedPPT was used as management system. Travel times were also a lot shorter than a few decades ago. Who would have thought that in 2051 it would take 32 minutes to travel from Enschede to Amsterdam in free flow conditions? However, these travel times also depended on the elected government, because travel speed was one of the decision variables used in SchedPPT. Not only the traffic system had changed, but also travelling itself had become more and more rare. Partly this was because the 4D video conferencing was nearly as good as being actually there.

PADdy continuous, “Tonight your wife will not be at home to have diner with you. Your diner will be served at 5.30 PM. What would you like to eat?” Luc answers, “It has been a long while since I ate French fries and a hamburger.” PADdy reacts “Your medical condition does not allow you to eat this food at the moment, please choose something else.” In 2030 the government decided that every Dutch inhabitant would get a chip injected that could monitor your medical condition and also contained all your personal information. Luc liked eating fast food now and then and especially when his wife was not at home, he grabbed this opportunity. However, his wife had made sure that his PADdy, which could order his dinner, would first check his medical condition. Fortunately, he knew some fast food restaurants near the destination in Enschede, so he would eat there. Because his wife could check his PADdy he answered “In that case, I would like to eat a salad.” Privacy continued to be a big issue when all these new technologies arose. Although, privacy was said to be secured, it was even more difficult to keep (little) secrets from your wife.

After getting dressed, Luc enters the kitchen. While enjoying his coffee, he scrolls through the news items presented at a big screen. “Cruijff foundation officially opens 14.000th Cruijff court, Mats Wismans Jr. scores decisive goal for the Dutch national soccer team, Hotel on the moon welcomes first guests, Water prices increases to 50 euro per barrel, ….”. After selecting a news item the news reporter starts “Today Twente University celebrates its 90th anniversary. Queen Amalia will actually visit Enschede to pay her respect to the many fine scientists…………………...” Luc started to dream about 40 years ago; a lot has changed since then. Back then you could retire when you were 65. Luc was already 75, grandfather of 14 grandchildren and still had to work for 2 more years. He missed some little things, like talking with collegues about a soccer game seen the day before on television, while standing in the coffee corner. He also missed driving a car and steering yourself. However, he did not want to be that old guy who stated “Everything used to be better”, because many problems were solved since then ………………….… “Your personalized public transport vehicle is ready for departure in 5 minutes”, PADdy says.

Contents

Chapter 1

Introduction

Je moet de bal hebben om te scoren
You need the ball, to be able to score
Johan Cruijff

The first chapter of this thesis presents the context, problem definition and research objective. It will point out that there is a need to optimize road traffic systems on network level and that dynamic traffic management measures are powerful tools to control traffic and are a serious option to reduce externalities. In addition, main practice is optimization of these measures on a local or corridor level and when a network approach is applied on strategic level, this approach is often based on an evaluation of a few predefined scenarios based on expert judgment. There is limited knowledge on how the various externalities interact and what strategies can be used to optimize them, taking into account the behavioral response of road users. In this chapter the research approach is presented as well. By formulating this optimization problem as a dynamic multi-objective network design problem, in which the dynamic traffic management measures are the decision variables and externalities are the objectives, the Pareto optimal set of strategic dynamic traffic management scenario can be determined. This set is obtained by solving an optimization problem, considering all possible scenarios, acknowledging the impact of traffic dynamics, anticipating the behavioral response of road users and considering all formulated objectives simultaneously. The Pareto optimal set contains valuable information, like trade-offs and achievable network effects, which is relevant for road management authorities to determine the best deployment of dynamic traffic management measures in a network. Based on this context, the problem and objectives are defined, the research approach and scope is presented and the contribution of this thesis is explained.

1.1 Context

In modern society, mobility is a basic human need and an important prerequisite for economic growth. Due to growing demand and difficulties to match supply, recurrent and non-recurrent congestion are part of daily traffic. As a result, traffic problems arise for society related to accessibility and livability. The challenge is to manage mobility in such a way that locations stay accessible and the negative effects, called externalities, such as pollution and accidents are minimized. The "Nota Mobiliteit" (Dutch Mobility Policy Document) therefore focuses on facilitating mobility growth and reducing externalities. Recently, there has been an increase in the attention paid to the traffic problems in our society, mainly in the context of climate, air quality and sustainability, which are of increasing importance when policy decisions are made. In the Netherlands this attention is further intensified, because in the past years several projects were blocked by the Council of State as a result of problems concerning air quality. Estimates by Annema and Van Wee (2004) show that the costs of congestion amount to 2-2.5 billion Euros, cost of accidents 4-8 billion Euros and environmental costs 3-8 billion Euros a year for the Netherlands. The costs of externalities are thus substantial, which emphasizes that externalities can not be neglected when managing mobility.

Traditionally, traffic problems are treated in isolation in terms of location and type of problem (e.g. accessibility, air quality and traffic safety). However, there is a strong spatial correlation between problems, so clearly solving a traffic problem at one location may result in other problems at other locations. Congestion problems on the main network can, for example, lead to "rat-running" (through-traffic using the secondary road network avoiding these congestion problems) causing also livability problems. Therefore, measures to alleviate traffic problems are nowadays increasingly focused on network level. In addition, solutions are sought for better utilization or even optimization of the road traffic system, which can be achieved using dynamic traffic management (DTM) measures.

DTM measures are road side or in-car measures, which settings can vary over time. These measures are used to inform road users (e.g. providing route information using variable message signs) or controlling traffic streams (e.g. metering traffic using traffic signals). These DTM measures are part of the broader class of intelligent transport systems (ITS) measures. The invention of the first traffic signal already took place in the 19th century and controlling traffic was then relevant to guarantee safety on intersections. Although safety issues are still reasons to implement traffic signals, these first DTM measures evolved to instruments that improve accessibility on a local level. At the end of the 20th century new measures were introduced, mainly on highways, as a result of the information technology revolution (e.g. variable message signs (VMS), rush hour lanes and ramp metering). Three levels of deployment of DTM measures can be distinguished. On an operational level, decisions are made by traffic operators or fully automatic in real time applications on the settings of the DTM measures, based on the current or short term predicted traffic conditions. On a tactical level, decisions are made by traffic engineers on the realization and usage of DTM measures for specific traffic conditions by providing a tactical framework. On a strategic level decisions are made by policy makers on the deployment of DTM measures to achieve certain policy objectives. Incorporating externalities as objectives for the deployment of DTM therefore starts on strategic level. The decisions on strategic level provide information about services, which is needed for the decisions on tactical level. On tactical level these services are translated into measures, procedures and algorithms that are used on operational level to actually inform and control traffic.

In research and in practice there has been a strong focus on operational and tactical level, which evolved from local approaches to (limited) network approaches to improve accessibility in which behavioral responses of road users are not taken into account. In practice network approaches are (optimal) control strategies for corridors in which (similar) measures are coordinated, based on measuring the current traffic situation (e.g. coordinated ramp metering on corridors or approaches coordinating traffic signals). In addition, there are multiple road management authorities that maintain and operate the available DTM measures in a network. Although there is a growth in cooperation between these authorities, this can be a bottleneck for realizing successful network approaches. There is little research on the application of DTM measures on strategic level. However, strategies can be important inputs to be able to implement successful network approaches. In practice various architectures have been developed in which formulation of these strategies is one of the aspects (e.g. European KAREN architecture (Bossom et al., 1999), the national ITS architecture of the United States (Lockheed Martin, 2012) and the Dutch traffic control architecture (Rijkswaterstaat, 2001)). However, in most cases these architectures focus on technical aspects. Within the Netherlands the formulation of strategies is often based on agreements made within a sustainable traffic management (STM) process, which is part of this Dutch traffic control architecture. In practice these strategies are often based on an evaluation of a few predefined scenarios based on expert judgment and the objectives are focused on accessibility. Even when externalities are considered, these are usually formulated as constraints (e.g. related to limit values of air quality) or not fully integrated as objectives (e.g. only specific roads are pointed out to be considered related to these objectives). This also means that these approaches evaluate alternative predefined strategies rather than generating alternative strategies optimizing the policy objectives and externalities are not fully integrated as such. In Bobinger (2008) it is also stated that due to the large number of possible solutions and the complex process of analysis and evaluations, the number of strategies in practice is reduced to a limited number of selected and evaluated solutions and therefore considered. The selection process of predefined scenarios however, lacks comprehensibility and transparency and fully depends on the expertise of traffic engineers, which may result in sub-optimal solutions. When it is possible to actually optimize the objectives formulated, it becomes possible to examine potential solutions systematically and comprehensively, because then all possible solutions are considered.

As mentioned, the deployment of DTM measures is focused on improving objectives related to accessibility, but minimizing externalities can be an objective as well. Different studies have shown that there is a proven relation between traffic dynamics and externalities. High speeds, significant speed differences between vehicles, and speed variation (accelerating, braking) have for instance a negative effect on traffic safety and emissions of pollutants (Rakha and Ahn, 2003; Aarts and Van Schagen, 2006; Beek et al., 2007; Barth and Boriboonsomsin, 2008; Can et al., 2009). Because DTM measures can influence traffic dynamics, these measures may also be used to minimize externalities. Within the "Nationaal Samenwerkingsprogramma Luchtkwaliteit" (national collaboration program air quality), which aims for improving air quality, DTM measures are also identified as promising measures for improving air quality as well as for improving noise (Ministerie VROM, 2008). In addition, the "Innovatie programma luchtkwaliteit" (innovation program air quality) concluded that DTM measures are useful measures to improve air quality (Spit, 2010). In a pilot study called "Dynamax" it is shown that variable speed limits (VSL) can be successfully implemented to reduce emissions and improve traffic safety (Ministerie van Verkeer en Waterstaat, 2010). Also in urban areas, there are some initiatives using DTM measures to reduce externalities. In Utrecht for example traffic signals that were used to meter traffic entering the Catharijnesingel, have been proven successful to alleviate air quality problems on this road. A pilot study in Zwolle proved that intelligent control of a single traffic signal can reduce emissions as well (Infomil, 2004). Besides economic objectives, the notion arises that DTM measures can also be used to improve livability objectives. Improvements are possible on a local level, where the traffic dynamics influences externalities, but also on a network level by influencing the amount of traffic using different road types. Minimizing externalities of traffic can therefore be interesting objectives for the determination of the deployment of DTM measures on strategic level, in which also the behavioral responses of road users (e.g. route choice effects) are taken into account.

Given the increasing attention on externalities and spatial correlation between problems, there is a need for multi-objective optimization of road traffic systems incorporating the externalities (Ministerie van Verkeer en Waterstaat, 2004; Wismans, 1999; AVV, 2002). DTM measures can be powerful instruments to better utilize or even optimize the road traffic system as well as instruments to reduce externalities. However, to be able to determine if externalities should be considered in the deployment of DTM measures, it is important to know how these objectives relate on network level. Considering multiple objectives in the deployment of DTM measures introduces new challenges, because the objectives related to accessibility and externalities can be conflicting and therefore not be optimized simultaneously (i.e. the optimal deployment of DTM measures for accessibility is not necessarily also optimal for air quality or noise). Research by Ahn (2008) for example showed that an emission optimized traffic assignment can significantly improve emissions over a user-equilibrium or system optimum traffic assignment. This indicates that these objectives indeed may be conflicting. Often formulated policy objectives to optimize all these objectives, are therefore probably not possible and policy decisions are needed how to weigh the various objectives. However, to be able to make these decisions, decision makers should know how the objectives relate and what the consequences are of certain decision. This type of knowledge is lacking on network level. Although it is acknowledged that DTM measures can be used to reduce externalities and also proven in theory and practice in various local applications on an operational level, there has been little research on the deployment of DTM measures optimizing multiple objectives related to accessibility and externalities on a network level incorporating road users behavior and therefore what strategies can be used.

1.2 Problem formulation and research objective

Given the observations in Section 1.1, incorporation of externalities as objectives, next to maximizing accessibility, for strategic DTM on network level, is a serious option. However, to be able to determine if these externalities should be part of the objectives, it is relevant to know how these objectives relate on a network level and to what extent DTM measures can influence these objectives. The behavioral responses of road users are an important aspect in this matter, which can not be neglected, especially on network level, because these responses will influence the possible effects. Earlier research already showed that the objectives are probably not all aligned. This means that when these objectives are considered, decisions are needed to weigh these objectives. In traffic and transport planning often cost-benefit analysis is used for this purpose, but it is uncertain if this method is useful for the decision at hand. Other methods are therefore possibly also of interest. To be able to make decisions on compensation principles, decision makers will also need information on how these objectives relate (conflicting or aligned) and what the possible effects and consequences are when a certain strategy is adopted (e.g. lower and upper bound and trade-offs). This way, decision makers can learn more about the problem before committing to a final decision (i.e. choosing a certain compensation principle). Knowledge on the relation between the objectives and on what kind of DTM strategies can be used to optimize certain externalities, is also useful for traffic engineers when faced with the challenge to address these objectives (e.g. to be able formulate a limited number strategies to evaluate for a specific case). However, knowledge on this matter is limited, especially for networks considering all externalities resulting from actual transport activities. This limited knowledge is also due to several challenges associated with solving this complex optimization problem. This thesis addresses some of the gaps and challenges related. Therefore the main research objective of this research is twofold and formulated as follows:

The objective of this research is to provide a suitable approach to optimize externalities as well as accessibility using DTM measures on a network level taking behavioral responses of road users into account to be able to provide insights in DTM strategies to optimize these objectives on a network level.

1.3 Research approach

Optimizing externalities and accessibility using DTM measures on a network level taking behavioral responses of road users into account, is a specific example of a network design problem (NDP). A NDP typically involves determining a set of optimal values for certain predefined decision variables, given certain constraints by optimizing different system performance measures, based on the behavior of road users. In this research the system performance measures are related to accessibility and externalities and the decision variables are the settings of DTM measures (i.e. the deployment of DTM measures). This optimization problem is a bi-level optimization problem, in which at the upper level road management authorities try to optimize certain system objectives. At the lower level, road users optimize their own objectives. Both levels are interdependent, because road management authorities determine the settings of the DTM measures based on the behavior of road users, and road users adapt their behavior based on the traffic conditions that are influenced by the DTM measures. This interaction results in a difficult optimization problem, identified as one of the most complex optimization problems in traffic and transport to solve (Yang and Bell, 1998). To be more specific, NDPs are a NP-hard problem (non-deterministic polynomial time hard problem). This generally means that heuristics are needed to solve them (Johnson et al., 1978). However, solving this optimization problem provides the optimal solution (in a single objective case) or Pareto optimal solutions (in a multi-objective case), comprising the best possible cooperative deployment of DTM measures on a network level, anticipating road users behavioral responses, considering all possible solutions.

To assess the performance of solutions (i.e. the outcome of the objective functions and constraints), the output of transport models can be used. Traffic assignment is the step in transport modeling in which trips are assigned to the network by confronting demand with supply, resulting in route choice, loads and traffic conditions. Different types of assignment models can be used for the assessments of measures, and can be classified into static and dynamic models. Static traffic assignment (STA) models describe the interaction between travel demand and infrastructure supply, assuming that demand and supply are time-independent, hence constant during the considered time period (stationary). The basic output of these models are link loads (amount of traffic using individual roads) and average link travel times or speeds. STA models are generally used at the strategic level in order to carry out long-term studies into effects of (mainly mobility-) measures. Dynamic traffic assignment (DTA) models are typically flow propagation models over time that calculate the resulting traffic conditions, taking changes in supply and demand over time into account. In general, DTA models are more suitable to estimate the effects of ITS than STA models, since time variability plays a significant role in most cases. In addition, the limitations of STA particular for over-saturated traffic conditions are widely recognized and DTM measures are often used to improve this kind of traffic conditions. In this case the usage of DTA models, or at least the dynamic network loading and according effect models to quantify the effects on externalities, is also needed to be able to address the effect of DTM measures on traffic dynamics and therefore externalities. Although literature is extensive, there are no standard methods to quantify the effects on externalities using DTA models. The usage of a DTA model also has implications for the solution approach, because these types of models are computationally expensive.

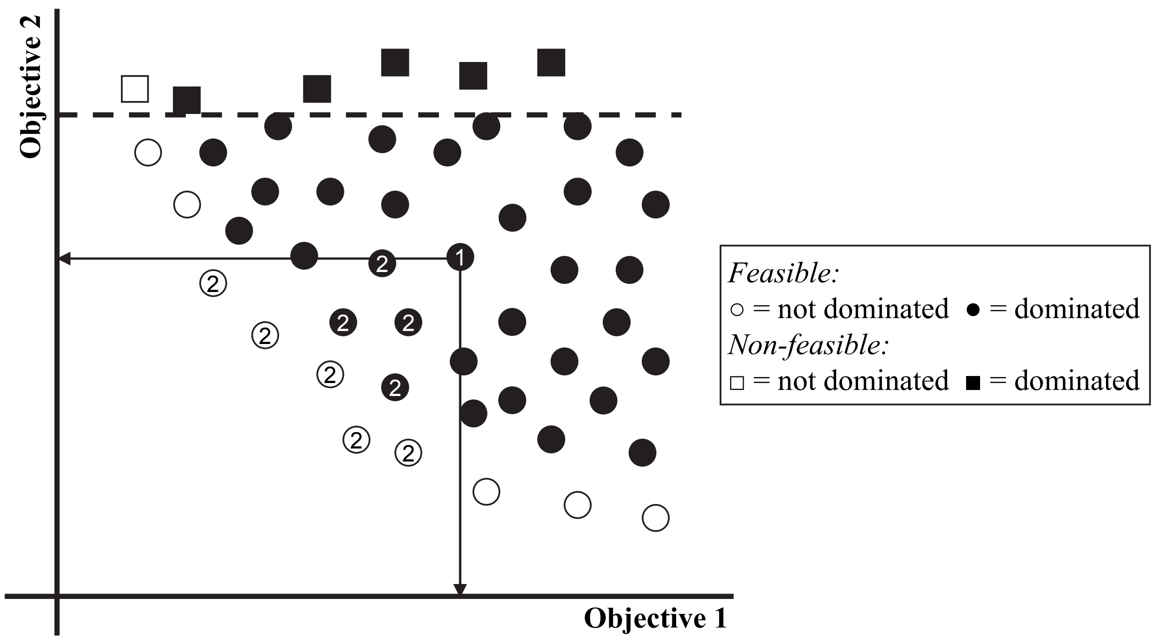

Figure 1.1 Example Pareto optimality

Often NDPs are focused on single objectives (i.e. SO NDP). However, in this research multiple objectives (MO) are involved, which means the optimization problem at hand is a MO NDP. As the name suggests multi-objective optimization, deals with more than one objective function. The presence of multiple possibly conflicting objectives makes the optimization problem interesting and more challenging to solve. In contrast to a single objective optimization problem, in which a single optimal solution can be found, solving a multi-objective optimization problem results in a set of trade-off optimal solutions known as Pareto optimal solutions. The Pareto optimal set consists of all solutions for which the corresponding objectives cannot be improved for any objective without degradation of another. Before explaining the concept of Pareto optimality further, the concepts solution space and objective space are introduced. Solution space, also called decision space, represents the space in which a solution is represented by its settings for all decision variables. For each solution in solution space, there exists a point in the objective space represented by its outcome on the formulated objectives. When constraints are considered, which can be related to the settings of the decision parameters, but also to the outcome on the formulated objectives, only a part of the solution space as well as objective space is considered to be feasible and forms the feasible set of solutions. In Figure 1.1 an example is presented of solutions in objective space considering two objectives both to be minimized. Solution 1 is represented by a point on the objective 1 and objective 2 axis. In this example an outcome constraint is assumed in which the outcome on objective 2 is not allowed to exceed a certain threshold. The solutions above this threshold are non-feasible, while all solutions beneath this threshold form the feasible set. All solutions can be further divided into two sets, those which are dominated and those that are not dominated. When a solution is dominated, there exist at least one other solution that performs better on (at least) one objective and not worse on all other objectives. Solution 1 is for example dominated by all solutions 2, because these solutions result in a lower value on objective 1 as well as objective 2. Some of the solutions are not dominated by any other solution. Hence, none of these non-dominated solutions can be said to be better than the other non-dominated solutions with respect to both objectives. These non-dominated solutions are the Pareto optimal solutions and the curve formed by joining these solutions is known as a Pareto-optimal front or efficient frontier.

The mapping between solution space and objective space is of interest. It is for example not necessarily true that solutions which are close to each other in objective space are also close to each other in solution space (e.g. two totally different DTM strategies resulting in similar performance on the objective functions). In the case of a multi-objective optimization problem it is therefore possible that Pareto optimal solutions can be found in all parts of solution space.

It is possible to formulate a single objective function that contains elements of all individual objectives (i.e. a weighted sum of all objectives). This means that the original MO NDP is formulated as a SO NDP. However, than it is assumed that the compensation principle is known in advance, which is not trivial. Steenbrink (1974) already concluded that it is impossible to formulate a single objective function in which all relevant factors are included completely and consistently. In addition, the Pareto optimal set contains valuable information, which makes it possible to address issues like the level in which the objectives are conflicting or not and what kind of strategies can be used to improve the effects on externalities. The Pareto optimal set therefore provides knowledge that is currently lacking when faced with the challenge to incorporate externalities as objectives to optimize DTM measures on a network level. Although the Pareto optimal set contains valuable information, in the end one compromise solution has to be chosen to implement. Analysis of this set is of interest for this decision, but also to gain general knowledge on using DTM measures on strategic level for these objectives. Choosing a compromise solution is related to multiple criteria decision making (MCDM) in which the best solution is chosen considering multiple objectives. The Pareto optimal set can be used as input for a powerful, interactive decision tool, allowing the decision makers to learn more about the problem before committing to a final decision. Analysis of the Pareto optimal set and this choice is rarely addressed in MO NDP literature, but necessary to select a DTM strategy in the end.

1.4 Challenges

The challenges in this research are first of all related to the objective of finding a suitable approach to solve the dynamic MO NDP in which externalities are incorporated. After these challenges are addressed, it is possible to focus on the main objective to provide insights in the consequences of optimizing externalities using DTM measures. The following challenges can be formulated:

Modeling framework
The bi-level optimization problem has to be formulated in a suitable modeling framework. This means formulation of objective functions, modeling of externalities connected with the

outcome of a DTA model, choosing a suitable DTA model and modeling of DTM measures and behavioral response.

Solution approach
To be able to find the Pareto optimal set of solutions and therefore providing insights in how DTM measures can contribute to reduce externalities on a network level, a solution approach is needed to solve this bi-level optimization problem. Because this is a difficult optimization problem that can not be solved exactly within reasonable time, heuristics are needed. However, there are various heuristics possible. Additionally, using a DTA traffic model to solve the lower level user equilibrium problem in combination with a heuristic is computationally expensive. Therefore, it is needed to select a suitable heuristic and to accelerate the approach where possible.

Decision support
When multiple objectives are considered, a compensation principle is needed to be able to choose the best compromise solution to implement. Solving the multi-objective optimization problem results in a Pareto optimal set of solutions, which can be used in a decision support system to learn about the problem and possible solutions before choosing a certain strategy. Choosing suitable methods to use within such decision support system is needed for this optimization problem.

Application
Applying the approach results in valuable information that can be used to formulate general recommendations, which can assist practice as well as research. The challenge is to provide insights in the relation between the objectives and what DTM strategies can be used to optimize the objectives, as is formulated as the main objective of this research.

1.5 Research scope

In this section the research scope is defined in the sense that some delimitations are discussed. These delimitations are mainly of importance for the modeling framework as will be presented in Chapter 4.

Behavioral response
The deployment of DTM measures will elicit behavioral responses of road users. In fact, the optimization should anticipate these responses to find the best solutions. The possible response depends on the extent in which the deployment of measures influences the aspects relevant for road user behavior, of which travel time and cost are considered to be the most important ones. The deployment of DTM measures will influence travel times and, also because externalities are incorporated as objectives, not necessarily in a positive way nor equally distributed. The main expected responses are route choice deviations and possibly changes in departure times. If the influence is large, even responses can be expected in modal split, destination choice or not making the trip at all. Because extreme strategies are not considered to be part of the feasible solutions in this research, these latter responses are not expected. Additionally, solving the dynamic MO NDP using heuristics is computationally expensive. Heuristics need many function evaluations and for every function evaluation the lower level optimization problem (i.e. the behavioral response of road users) has to be solved. Therefore, in this thesis only the main behavioral response of route choice is considered, which is operationalized by solving the (stochastic) dynamic UE problem

Measures

In this thesis the focus is on the deployment of DTM measures on strategic level considering behavioral responses. In this case the DTM measures considered are traffic control measures, which means only measures are considered that road users have to comply with and actually influence supply of infrastructure. DTM measures focusing on providing traffic information are thus not considered. However, such measures are especially of interest in non-recurrent situations and not in this case, in which it is assumed that road users will behave according to Wardrop’s first principle of equilibrium, wherein no driver can unilaterally change routes to improve his/her travel times. In this research a stochastic dynamic UE problem is solved when assessing the effects of implementing a certain deployment of DTM measures, which means no driver can unilaterally change routes to improve his/her perceived travel times.

On a strategic level it is also of interest to consider realizing new measures as a possible option. This would introduce additional constraints in the optimization problem, technical (i.e. possible DTM measure-location combinations) and budget (available investment budget). Although of interest, in this thesis it is assumed that the objectives are optimized using the available DTM measures in a network.

In this research only road traffic is considered and no distinction is made in measures for certain specific vehicle classes. This means for example, that bus priority or specifice traffic management measures for trucks are not part of the possible measures to optimize externalities.

The main interest of this research is to determine the strategies that optimize the objective functions. This means for example that it is not necessary to know the exact parameter settings of a traffic signal (e.g. cycle length and green times), but it suffices to know if traffic should be metered or the throughput should be improved and to what extent. The actual translation to the actual parameters of the DTM measures can be done afterwards. Because of this, but also because there are DTM measures for which the decision variables are discrete, the optimization problem is considered to be a discrete NDP (DNDP). Additionally, the optimization is not only on a strategic level, but also on network level and performed off-line. This means that the local deployment of a certain DTM measure can be tuned in such a way that the local performance is non-optimal and is focused on anticipating the behavioral response. Therefore, the measures will be deployed time-dependent, which means the settings of the DTM measures considered, are altered over time, and not traffic responsive in a sense that the DTM measures automatically operate based on the current traffic conditions. However, DTM measures that are taken into consideration are possibly a subset of the total number of DTM measures available to limit the decision variables. If this is the case the DTM measures chosen will be the main measures available to control traffic. Other DTM measures are assumed to optimize based on the local traffic conditions and are therefore modeled traffic responsive. This way the other DTM measures will not counteract the strategies chosen and the results will be closest to reality in which, at least in the Netherlands, actuated control is the most widespread form of traffic control.

Demand

Because only route choice is considered, elastic demand is not assumed. However, in reality also day-to-day variability exists, which means demand can vary every day. Neglecting this variability, which is done in this thesis by assuming fixed demand, means that the robustness of DTM strategies is not part of the optimization approach. It is assumed that the optimization of DTM measures for the average demand situation results in suitable strategies and is not extremely sensitive for day-to-day variability. This assumption is in accordance with the assumptions made for measures, because the solutions considered are strategies, but is not necessarily true.

Objective functions
All objective functions will be formulated as a network performance measure per objective. There are mainly two externalities considered in this research for which the local effect is relevant. For air quality as well as noise, the number of people who are affected is of interest. Additionally, there are European limit values or legislation that any road authority is obliged to take into account. In this thesis the objective functions formulated, will all be on the network performance and not focusing on limit values. Next to complexity issues, there are also other reasons to do so. First of all, DTM measures can help to reduce concentrations or noise levels, but are not the main measures to comply with European legislation. Second, the objective of road authorities should not be to comply with legislation, but to improve the livability as best as possible. In this research these externalities are therefore considered to be objectives instead of constraints. Finally, in planning processes, in which often cost benefit analysis is used, these externalities are also taken into account based on their network effects.

Modeling
Starting point of this research is the use of existing DTA models and available models or knowledge to model the externalities. Hence, no new experimental or real-life observations have been gathered to build or improve existing models. The focus is on the best interconnection between these models, the solution approach and application.

1.6 Thesis contributions

The research to be elaborated in the next chapters, succeeds in providing a number of contributions on optimizing road traffic system using DTM measures incorporating externalities as objectives. These contributions are summarized as follows:

Solution approach
Solving the MO NDP is a complex optimization problem that is computationally expensive. In this research the general framework is formulated in an efficient new way. Several promising multi-objective optimization methods are developed and compared for the MO NDP including approaches to accelerate the optimization process.

Quantifying externalities using DTA models
In this research an extensive literature review is carried out to be able to select the best methods to quantify the externalities. These methods are connected to a DTA model in this research and appropriate general objective functions are formulated. This research provides for the first time a framework in which noise, traffic safety, air quality, climate and efficiency (as a measure for accessibility) can be assessed using a macroscopic DTA model, taking traffic dynamics into account.

Methods to support decision making process
The Pareto optimal set contains valuable information for the decision making process. In this research analysis of the Pareto optimal set and possible ways to reduce this set to maintain a smaller set is addressed. In this research the consequences of monetizing externalities are addressed as well as the advantages and disadvantages of several other MCDM methods. This step is rarely addressed in MO NDP literature and this research makes a step forward by

combining various methods, which is useful to choose appropriate methods for this type of problem.

Results of multi-objective optimization
Using case studies the consequences of optimizing externalities using DTM measures is analyzed to provide actual insights on how the objectives relate, what kind of DTM strategies can be used to optimize certain externalities and what the consequences are when certain strategies are adopted. This dynamic multi objective optimization of externalities using DTM measures on a network level and analysis of the results in test cases has not been earlier addressed.

1.7 Outline of thesis

This thesis is structured as follows. In Chapter 2, an overview is presented on DTM and NDP. The overview on DTM is to provide some more information about earlier research on optimizing DTM measures and current practice. The overview on NDP provides information on the characteristics of these kinds of problems, in which special attention is paid on the solution approaches used in these earlier studies. This second chapter provides additional information to understand the challenges for this research, which are presented in Chapter 1 as well as the scope. The third chapter provides background information on externalities and a review on modeling externalities using DTA models. This information is relevant to understand which methods and objective functions are chosen in the solution approach. Chapter 4 presents the general framework, providing the mathematical formulation, chosen methods to quantify the externalities, the general objective functions, the way the DTM measures are modeled and a short description of the used DTA model and why this model was chosen for this research. The fourth chapter also introduces the test cases used in this research and which will be referred to throughout this thesis. The fifth chapter addresses the solution approach. It contains a comparison of various heuristics to solve the formulated MO NDP and the performance measures used. Additionally, it also contains a comparison of solution approaches in which the heuristic is combined with a response surface method to accelerate the optimization process and an explanation of additional possibilities. In Chapter 6 it is explained what kind of information is contained by the Pareto optimal set and methods are presented and compared to reduce the Pareto optimal set (called pruning). After presenting the consequences of monetizing the effects, several other MCDM methods are presented and deployed to discuss the advantages and disadvantages of these methods. The final test cases, which are used to show the results of an optimization and therefore what can be learned of such an optimization, are presented in Chapter 7. Finally, in chapter 8 the final conclusions are stated, as well as possible interesting directions for further research.

Chapter 2

Background

De ervaringen van gisteren zijn de doelen van morgen
The experiences of yesterday are the objectives of tomorrow
Johan Cruijff

In chapter 1 the context, problem formulation, research objectives, challenges, scope and thesis contributions are defined. The objective of this research is to provide insights in how DTM measures can contribute on improving externalities on a network level and to provide a suitable approach to optimize these objectives using DTM measures on a network level taking behavioral responses of road users into account. This optimization problem is a specific example and can therefore be formulated as a multi-objective network design problem. This chapter provides background information on DTM and NDPs. This chapter will point out that research on the simultaneous optimization of externalities incorporating traffic dynamics using DTM measures is not addressed earlier. Additionally, it is found that global optimization of DTM measures generally results in significant better solutions than local optimization and using DTA models is more appropriate than using STA models. However, NDP research is focused on optimization of single objectives and usage of STA to solve the lower level problem. Formulating the optimization problem as a dynamic MO NDP is therefore most appropriate, but not considered earlier.

2.1 Dynamic Traffic Management

2.1.1 Introduction

DTM traditionally aims at improving traffic conditions at certain locations or on a network level by directly influencing throughput using road-side measures or influencing behavior of road users by providing travel time information. As indicated in Chapter 1, three levels of deployment of DTM measures can be distinguished. On an operational level, decisions are made by traffic operators or fully automatic in real time applications, on the settings of the DTM measures based on the current or short term predicted traffic conditions. On a tactical level, decisions are made by traffic engineers on the realization and usage of DTM measures for specific traffic conditions by providing a tactical framework. On a strategic level, decisions are made by policy makers on the deployment of DTM measures to achieve certain policy objectives. The decisions on strategic level provide information about services, which are needed for the decisions on tactical level. On tactical level these services are translated into measures, procedures and algorithms that are used on operational level to actually inform and control traffic.

The deployment of DTM measures will elicit behavioral responses of road users, as is the case in most interventions, because these measures will influence traffic conditions. In general, the behavioral responses as a result of changing supply of infrastructure can vary between changes in routes or departure times via changes in mode or destination, which people are less willing to change, to changes in car ownership or residential location, which people are least willing to change. The extent in which these behavioral responses occur, depend of the extent of the interventions. However the willingness in changing also depends of the road user and the purpose of travel (e.g. it may be easier to change destination for leisure than business activities). It is likely that the deployment of DTM measures on network level will mainly affect route choice and departure time choice. In most research on the deployment of DTM measures only route choice effects are taken into account or all behavioral responses are neglected.

Although, research on operational and tactical DTM is extensive, in Dutch practice the measures operate automatically on-line based on predefined plans and actual measurements on a local level or are to some extent coordinated. These plans or algorithms are in most cases off-line optimized for recurrent situations (i.e. based on average demand) aiming at objectives related to accessibility (e.g. minimizing delay) and can adjust to some extent based on the current traffic situation in the case of actuated control. Behavioral responses of road users as a result of a certain deployment of DTM measures are often not considered. In case of non-recurrent traffic conditions, traffic operators have to intervene by selecting the most appropriate control plans available or changing parameters. However, in current practice this is rarely done. Some of the available DTM measures are mostly used to improve traffic safety. The Dutch motorway traffic management (MTM) system, for example, uses VMSs to inform upstream traffic about congestion by reducing speed limits. Another example is the use of traffic signals to provide possibilities for pedestrians to cross the street. In scientific research there has been more research on optimal control algorithms for (limited) network approaches and the incorporation of externalities as objectives which will be addressed in the next section (Section 2.1.2). On strategic level, current practice is more focused on the process of developing DTM strategies. The STM process part of the Dutch national traffic management architecture is an example (AVV, 2002). This approach has been developed in the beginning of 2000 and although the name contains sustainable, addressing externalities was not explicitly part of this approach till recently. This approach aligns with the European KAREN architecture but is slightly more user oriented (Taale et al., 2004). The approach provides a framework for cooperation of the various road management authorities on a regional level to deploy DTM measures on a strategic level, based on jointly formulated objectives. Outcome of this process are objectives, control strategies, problems and measures (existing or new). Reasons for starting such a process can be recurrent traffic situations or expected non-recurrent traffic situations (mainly lengthy road works). The STM approach originally focused on objectives concerning accessibility. In the past few years some efforts have been made to incorporate other objectives related to externalities as well. In Wilmink and Beek (2007) for example some concepts are presented concerning the incorporation of externality objectives within the STM approach of the Dutch government. It involves formulating objectives, use information about the current state on these objectives to change priorities within the network, setting link thresholds on these objectives and defining a possible strategy to resolve the bottlenecks (externalities inclusive). However, it has never been applied. Recently, an update of STM called STM plus, has been launched in which livability and traffic safety are more explicitly considered by taking the functions of the various roads within the network into account (Adams and Van Kooten, 2011). This means that within the strategies proposed as a result of this approach, DTM measures are also deployed to improve traffic safety and livability on certain roads. The STM approach is mainly based on expert judgment to formulate the strategies. Theste strategies are then tested using traffic models to choose and fine tune the best one. Scientific research on developing DTM strategies is limited, and is mainly focused on optimal deployment of measures on network level considering route choice behavior, again focusing on objectives related to accessibility only. This will be addressed in Section 2.1.3.

2.1.2 Research on optimal control, not considering route choice

Most research on the deployment of DTM measures is related to optimal control in which the behavioral responses are not considered. The deployment of DTM measures can be a result of an optimization procedure or are control algorithms in which the deployment of DTM measures depends on measuring current or predicted traffic conditions. Most early research on this subject is related to optimizing accessibility to determine the settings of traffic signals off-line, based on average demand. This started with fixed-time control strategies on local level, of which the Webster formula is a well known example. Also the coordinated traffic control focused on traffic signals of which TRANSYT, SCOOT and UTOPIA are well known programs used off-line as well as on-line (Taale, 2008; Van Katwijk, 2008). Research on adaptive optimal traffic signal control is an active research field also on local level, however the wide scale implementation of such systems is not yet the case. The majority of the signal controllers in use is still fixed or traffic actuated and operated in a time-of-day mode (Yin, 2008).

Research on optimizing objectives using DTM measures in which possible behavioral responses are neglected, is extensive. In Stevanovic et al. (2008) signal timing parameters and transit signal priority parameters are the decision variables and total delay the objective function, which is optimized using VISSIM and a genetic algorithm (GA) as an extension of TRANSYT. Chow and Lo (2007) developed a derivative based heuristic algorithm for dynamic traffic control in which minimizing total delay is the objective and showed the feasibility of their approach. In their optimization approach a set of travel delay derivatives are developed and combined with a Frank-Wolfe algorithm as an initial step of a GA to start with a seeded initial population. In Park and Kamarajugadda (2007) a stochastic traffic signal optimization method is presented in which highway capacity manual (HCM) delay equations are used in combination with a GA and stochastic demand to optimize signal settings optimizing average delay. Memon and Bullen (1996) investigated optimization strategies for real-time traffic control signals in which minimizing total stopped delay was the objective. In this research a GA outperformed the Quasi-Newton gradient search method on efficiency and effectiveness. Abu-Lebdeh and Benekohal (2000) formulates the dynamic signal control and queue management problem and uses a GA to find optimal control in which maximizing the systems output is the objective. Osorio and Bierlaire (2011) propose a trust region optimization algorithm, using a surrogate model based on queueing theory within a microscopic simulation framework, for solving a fixed-time signal control problem minimizing total travel time and showed the added value of using this surrogate model for small sample sizes. The question arises if heuristics like GA can also be used in on-line applications on large-scale networks. Therefore Dinopoulou et al. (2006) and Aboudolas et al. (2009) presents an responsive urban traffic control strategy in which a store-and-forward based approach is used to efficiently minimize the link's relative occupancies. Biollot et al. (2006) also present a real-time urban traffic control system, CRONOS, that can be used for single or coordinated control to minimize total delay. The solution approach is a heuristic (modified version of the Box algorithm) that only investigates a few solutions to search for a good local optimum. Comparison performed by the authors with usual control strategies, showed promising results for the CRONOS algorithm. Agent based models, which are for example developed and tested in Van Katwijk (2008) and De Oliveira and Camponogara (2010), for predictive signal control in urban traffic networks are also likely to be better scalable and therefore more suitable to use for on-line applications.

Next to the focus on traffic signal control, there has been done limited research on the coordination of different or other types of DTM measures. In Meng and Khoo (2010) for example optimal coordinated ramp metering control is investigated in which total delay and equity are the objectives. Papageorgiou (1995) presented an integrated control approach for traffic corridors that can deal with DTM measures like ramp metering, signal control, route guidance and VMS minimizing total travel time. In Papamichail et al. (2008) and Carlson et al. (2010) optimal control using VSL and ramp metering minimizing total travel time is studied and showed that the efficiency can be substantially improved.

In all but one exception, the discussed studies thus far and also in most cases consider a single objective function related to accessibility (e.g. maximizing throughput or minimizing delays). However, in Meng and Khoo (2010) an additional objective related to equity was incorporated for fair ramp metering control. In this research a dynamic network loading (DNL) model is used in combination with a multi-objective GA to solve the multi-objective optimization model. The research presents the possible trade-offs between minimizing delay and maximizing equity. A GA was also used in Anderson et al. (1998) to optimize a fuzzy logic traffic signal controller (i.e. the parameters of the fuzzy logic membership functions used to allocate the green times). Within this study the evaluation of the controller for a single traffic signal was carried out using VISSIM microscopic traffic simulation. This study presented the Pareto optimal set of solutions optimizing the objectives traffic delays and emissions. The same approach was used in Schmocker et al. (2008), however in this case for multiple traffic signals and multiple objectives related to the delays for different road user classes including vulnerable road users. This research also presents a procedure for a rarely addressed step about choosing a specific solution to implement. This procedure is based on the Bellman-Zadeh principle. This approach seeks to maximize the minimum satisfaction with respect to all the objectives, based on a function expressing the satisfaction per objective.

There have also been some efforts to incorporate objectives concerning externalities of traffic. In Murat and Kikuchi, 2006, a fuzzy optimization approach is presented and tested for optimal signal timing settings in which delay and fuel consumption were the objectives. The HCM equations, Webster's method and the Akcelik method were compared for the traditional formulation and fuzzy formulation. Zegeye, 2011 used a weighted sum of total travel time, emissions and fuel consumption to determine the optimal control strategy of deploying VSL and ramp metering. In this research the modeling framework was formed by a combination of the METANET macroscopic DNL model and the Virginia Tech microscopic energy and emission model (VT-micro model). The used optimal control strategy in this research resulted, according to the authors, in a balanced trade-off between travel time, emissions and fuel consumption. Lv and Zhang (2012) investigated the effect of signal coordination on traffic emissions (CO, HC and NO) using the VISSIM microscopic simulation model and emission model MOVES. They concluded that the impact of cycle length on delay is more significant than on stops and emissions for under-saturations traffic conditions. In Zito (2009) a similar effect was found for signal coordination. In Lv and Zhang (2009) it was also found that given a fixed cycle length, it is possible to reduce delay, stops as well as emissions.

The only research found in which route choice effects are not considered, an externality is incorporated as an objective and a true multi-objective optimization is performed, is by the earlier mentioned Anderson et al. (1998) for a single traffic signal. In almost all cases a single objective related to accessibility is used to optimize mainly traffic signals on a local or corridor level. Another interesting observation is that in all recent research on the optimization of DTM measures in which route choice is not considered a dynamic traffic model is used, microscopic as well as macroscopic. This is of interest because in research in which route choice effects are considered, this is rarely the case.

2.1.3 Research on optimal control, taking route choice into account

Next to the extensive research on optimal control, in which the behavioral response are not considered, there is, although limited, also scientific research on the optimization of the deployment of DTM measures taking into account the route choice effects. When considering route choice effects, the optimization problem, becomes a bi-level optimization problem, which can be formulated as a NDP.

A part of early research on DTM optimization is on calculating mutually consistent traffic signal settings and link flows. In the first approaches the signal settings and link flows were calculated by solving the signal settings problem for assumed link flows and by solving the static UE problem for the resulting signal settings sequentially until convergence was achieved (e.g. Allsop and Charlesworth, 1979). This approach is called the iterative-optimization-assignment approach. Gershwin (1978) also proposed such an approach in which not only route choice but also the modal split was part of the optimization process. However, the resulting mutual consistent signal settings and equilibrium flows will not result in finding a global optimum for the system as a whole (Dickson, 1981; Ceylan and Bell, 2004; Gartner and Al-Malik, 1996) and dependent on the delay functions used does not necessarily minimize travel times especially in over-saturated networks (Dickson, 1981; Yang and Yagar, 1995). To be more precise, this procedure does not necessarily converge to the exact solutions of Stackelberg games, but is an exact and efficient algorithm to solve Cournot-Nash games when using appropriate delay functions. This means that each player (upper level of road management authorities and lower level of road users) attempts to maximize its objectives non-cooperatively and does not assume that its action will have an effect on the actions of other players. However, the objectives of the upper level player can be higher if it anticipates on the (predicted) response of the lower level (Yang and Bell, 1998; Chen and Ben-Akiva, 1998). In Ceylan and Bell (2004) a traditional mutually consistent solution using the iterative-optimization-assignment approach was compared with an approach in which global traffic signal optimization was performed using a GA (i.e. assuming Stackelberg game). The upper level problem is on optimizing cycle times, offsets and green times and the lower level the stochastic UE problem. The objective function used was a weighted linear sum of delay and number of stops. In this research the optimal solution found, significantly improved using this approach compared with the mutual consistent solution. Other research that also assumes local optimization of signal settings formulates the optimization of signal settings as an asymmetrical equilibrium assignment problem (e.g. Cantarella et al., 2006; Cantarella and Vitetta, 2006; D'Acierno et al., 2012). Cantarella et al. (2006) compared various heuristics (hill climbing, simulated annealing, tabu search, GA and path relinking) for the optimal lane layout and signal setting problem. The optimization problem was formulated as a NDP and the objective the minimization of total travel time. However, in this research the signal settings are locally optimized using the Webster method, while solving the UE problem, which means by solving an asymmetrical equilibrium assignment problem. Because of the local optimization and used solution approach, no coordination is considered. This also means that the true decision variables optimized using the heuristics are the lane layouts and the signal settings are changed to facilitate the equilibrium flows best as possible. In Cantarella and Vitetta (2006) the same optimization problem is considered using the same decision variables, however in this case for the multi-objective NDP and considering multiple modes. The optimization is performed using a GA and the objectives total travel time on car and bus, total travel time on pedestrian links, and global emission of CO. A subset of the resulting Pareto optimal set is presented in this research using cluster analysis. D'Acierno et al. (2012) also focused on solving the asymmetrical equilibrium assignment problem and proposed ant colony optimization to accelerate solving this problem. In Cascetta et al. (2006) local optimization approaches formulated as asymmetrical equilibrium assignment problem and global optimization approaches formulated as bi-level optimization problem are compared. In this research it is shown that the global optimization approaches show significant better results in terms of lower values of total travel times, which is used as objective function. In this research STA is used to determine equilibrium flows.

Next to Ceylan and Bell (2004) and Cascetta et al. (2006), also earlier research has been done in global optimization of the signal setting problem. Yang and Yagar, 1995 for example used gradient methods to solve the global optimization of signal settings and traffic assignment. Cipriani and Fusco (2004) also proposed gradient algorithms. However, this type of methods can still end up in a local optimum. Sadabadi et al. (2008) proposed a method for optimizing signal settings as well. In this case the original NDP is relaxed by the system optimal flow pattern proposing a lower bound. This relaxed NDP can be solved efficiently using a steepest descent method. Using system optimal flow is justified by the authors, because user optimal and system optimal flow patterns are quite similar under both non-congested and highly congested conditions. Although this is true using a STA formulation, it can be argued if such traffic conditions are prevalent in reality especially when there is a need for optimizing DTM measures on network level. Afandizadeh et al. (2012) formulated the signal setting problem as a NDP and used simulated annealing to minimize total travel time. Chiou (2005b and 2007) reformulates the NDP optimizing traffic signals (cycle time, start and duration of green times) in a single level optimization problem using a sensitivity method to obtain derivatives. This problem is solved using subgradient methods showing promising results. In Chiou (2005b) more information on solution approaches of the combined problem of signal setting and network flow using STA is presented. Although almost all research related to optimization of

DTM measures in which route choice effects are considered, is on traffic signal control, Yang and Yagar (1994) investigated optimal ramp metering in freeway networks formulated as a continuous NDP (CNDP). In this research sensitivity analysis was used to formulate derivatives, which are used to minimize total travel time using ramp metering.

All research presented thus far used STA models to determine the route choice effects. Chen and Ben-Akiva (1998) is one of the rare research found in which a DTA model is used to optimize traffic signals taking into account route choice effects. In this research the authors formulated the problem in three different ways, the Cournot game (optimization by players without knowing the other's strategy), the Stackelberg game (the leader anticipates the user optimal strategy) and a monopoly game (there is one player that controls the signal settings and traffic flows). The latter is an unrealistic game in which the upper level can also dictate traffic flows resulting in a system optimal traffic situation, but is used as a benchmark. The Cournot game results in mutual consistent flow and can be formulated as a single level optimization problem. The second approach formulated as a bi-level optimization problem results in optimal settings for the objective of the upper level given the behavioral response of the lower level (i.e. NDP formulation) and is superior in optimizing the objective of the upper level (i.e. minimizing total travel time). Comparison with a fixed control strategy based on average traffic flows and the Webster method (similar with using STA) shows that both strategies can improve network performance significantly. Abdelfatah and Mahmassani (2001) as well as Chen and Hu (2009) used a DTA model as well, but both optimized signal settings on a local level. Chen and Hu (2009) solved this problem as an iterative-optimization-assignment approach and Abdelfatah and Mahmasani (2001) as an asymmetrical equilibrium assignment problem. Karoonsoontawong (2009) used simulated annealing, GA and reactive tabu search, while Sun et al. (2006) used a GA to optimize the bi-level optimization problem using DTA and total travel time as objective function.

Almost all research found on the optimal deployment of DTM measures in which route choice effects are considered use STA and are related to the optimal signal setting problem. The formulation of this optimization problem as an asymmetrical equilibrium assignment problem is often used, because computation times are lower than solving a bi-level optimization problem. However, this approach can not be used for multi-objective optimization problems and generally results in less performing solutions. Research in which DTA models are used is limited, especially when global optimization is performed. All research found, use a single objective related to accessibility.

2.1.4 Conclusions and discussion

Research on the deployment of DTM on network level is mainly focused on operational or tactical level and in most cases still considers a single objective related to accessibility. Research can be divided into optimization in which the behavioral response is taken into consideration and which do not. In almost all research only route choice effects are considered as behavioral responses of road users. When route choice is considered mainly STA is used to model route choice effects, while if route choice is not taken into account mainly dynamic traffic models are used. There are only a few studies in which various DTM measures are considered to deploy in cooperation. The DTM measures mainly considered are traffic signals. Almost none of the research found consider multiple objectives and no research is found considering multiple objectives and behavioral responses. Although it is acknowledged that global optimization results in better solutions, local optimization has been studied extensively. A possible explanation of the main focus on local optimization as well as the use of STA, is the needed computation times for global optimization and applying DTA models.

The state-of-practice of strategic DTM is mainly based on expert judgment in which a limited number of strategies are considered. Although the importance of externalities is acknowledged in practice, the combination of these objectives is not considered. Knowledge on how DTM measures can be deployed to optimize the externalities simultaneously on network level is lacking, but can be useful to support the process of formulating and choosing appropriate strategies.

2.2 Network Design Problem

2.2.1 Introduction

Road network design problems (NDP) typically involve determining a set of optimal values for certain predefined decision variables by optimizing different system performance measures taking users' route choice behavior and certain (budget) constraints into account. The predefined decision variables can be any variable connected with the design of a network, which means concerning the supply of infrastructure (e.g. new road infrastructure, changing existing road infrastructure, pricing measures or DTM measures). The constraints considered, are usually the budget for investment consisting of the monetary upper bound that the system manager is willing to invest in building a certain network configuration. However, additional constraints are possible like the maximum level of emissions from vehicles that the community is willing to accept or constraints related to equity. The NDP is generally formulated as a bi-level optimization problem (see Figure 2.1) or the equivalent mathematical problem with equilibrium constraints. In this bi-level optimization problem, the upper level describes the optimization of the overall system performance function in the single-objective case (SO NDP) or functions in the multi-objective case (MO NDP). On the upper level, the decision maker aims at optimizing these objectives and controls the decision variables. The lower level describes the behavior of road users, who optimize their own objectives and therefore the reaction of the road users on the measures taken at the upper level. Since the upper level cannot dictate road user's behavior, the decision made at the upper level also depends on this reaction. Although often only route choice behavior is considered also other behavioral effects like departure time choice or mode choice can be relevant. In addition, the upper level often consists of one decision maker, although in practice there can be many decision makers with different objectives (e.g. several road management authorities) and each with their own decision variables. In the latter case the NDP becomes a multi-level optimization problem in which the decision makers also influence each other (Ohazulike et al., 2012). Because the NDP is NP-hard, heuristics are generally used to solve the NDP (Johnson et al., 1978; Yang and Bell, 1998; Gao et al., 2005; Chiou, 2005a).

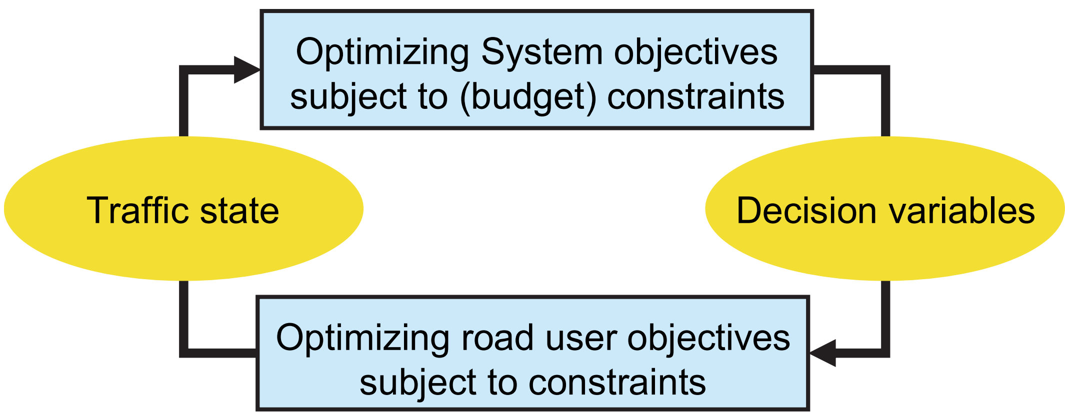

Figure 2.1 Bi-level optimization problem

2.2.2 Historical perspective on NDP

Steenbrink (1974) is one of the first authors that has addressed road NDPs. Since then numerous studies on NDP have been reported in literature. The NDPs are typically grouped into discrete problems (DNDP), in which the decision variable is a discrete variable, continuous problems (CNDP), in which is assumed that the decision variable is a continuous variable, and mixed problems (MNDP), which is a combination of both. As indicated in Boyce and Janson (1980) and Poorzahedy and Turnquist (1982) the DNDP formulation is often more appropriate since the continuous functions permit the solution to include fractions of highway lanes. In general, the CNDP is easier to solve, because this problem can be formulated as a single level optimization problem by calculating the derivatives of the traffic assignment results by some sensitivity analysis method for equilibrium network flow (Yang and Bell, 1998), which will be discussed later. Based on demand, NDPs can be grouped into fixed demand, stochastic demand and (stochastic) elastic demand.

Table 2.1 Examples of NDP

Class*	Type	Examples
Decision variable	Discrete	Boyce and Janson, 1980, Drezner and Wesolowsky, 2003; Gao et al., 2005; Jeon et al., 2006; Poorzahedy and Turnquist, 1982; Los and Lardinois, 1982
	Continuous	Steenbrink, 1974; Abdulaal and Leblanc, 1979; Abdulaal and Leblanc, 1979; Leblanc and Abdulaal, 1979; Ban et al., 2006; Chen et al., 2003; Chen and Yang, 2004; Waller and Ziliaskopoulos, 2001; Chiou, 2005a; Dantzig et al., 1978; Friesz et al., 1993; Meng et al., 2001; Xu et al., 2009; Karoonsoontawong and Waller, 2005; Zhang and Lu, 2007; Ceylan and Bell, 2005; Chen et al, 2010; Ukkusuri and Patil, 2009.
	Mixed	Cantarella et al., 2006; Cantarella and Vitetta, 2006; Luathep et al., 2011
Demand	Fixed	Drezner and Wesolowsky, 2003, Gao et al., 2005; Jeon et al., 2006; Poorzahedy and Turnquist, 1982; Meng et al., 2001; Cantarella et al., 2006; Los and Lardinois, 1982; Steenbrink 1974; Abdulaal and Leblanc, 1979; Leblanc and Abdulaal, 1979; Ban et al., 2006; Chiou, 2005a; Dantzig et al., 1978; Xu et al., 2009; Zhang and Lu, 2007; Karoonsoontawong and Waller, 2005; Viti et al., 2003; Karoonsoontawong and Waller, 2006;
	Stochastic	Waller and Ziliaskopoulos, 2001; Ceylan and Bell, 2005; Chen et al., 2003; Chen and Yang, 2004, Chen et al, 2010; Karoonsoontawong and Waller, 2007
	Elastic	Boyce and Janson, (1980), Cantarella and Vitetta, 2006; Santos et al., 2009; Ukkusuri and Patil, 2009
Time	Static	Boyce and Janson, 1980; Drezner and Wesolowsky, 2003; Gao et al., 2005; Jeon et al., 2006; Poorzahedy and Turnquist, 1982; Los and Lardinois, 1982; Steenbrink, 1974; Abdulaal and Leblanc, 1979; Leblanc and Abdulaal, 1979; Ban et al., 2006; Chen et al., 2003; Chen and Yang, 2004; Chiou, 2005a; Dantzig et al., 1978; Friesz et al., 1993; Meng et al., 2001; Xu et al., 2009; Zhang and Lu, 2007; Cantarella et al., 2006; Cantarella and Vitetta, 2006; Ceylan and Bell, 2005; Ukkusuri and Patil, 2009
	Dynamic	Waller and Ziliaskopoulos, 2001; Karoonsoontawong and Waller, 2005; Viti et al., 2003; Karoonsoontawong and Waller, 2006; Karoonsoontawong and Waller, 2007; Brands et al., 2009; Li et al., 2009

*Not mutually exclusive

Stochastic demand is of interest to incorporate robustness of solutions in the NDP and if elastic demand is needed, also depends to what extent behavioral effects can be expected as a result of a certain implementation. Based on the way time is considered, NDPs can be classified into static, in which stationary travel demand and infrastructure supply is assumed, or dynamic, which is rarely used. In Janson (1995) it was demonstrated that an approach capturing traffic dynamics provides more flow-consistent solutions than static approaches for the NDP (i.e. taking into account traffic interaction among adjacent links). In Karoonsoontawong and Waller (2007) it is also stated that the use of STA has several drawbacks related to capturing the traffic interaction among adjacent links and the use of steady-state time-invariant demand, leading to suboptimal solutions. In Table 2.1 examples are provided of the various types of NDP.

Objective functions and constraints
Traditionally, the NDP is associated with the optimization of accessibility using infrastructural investment decisions under a budget constraint. Generally these studies solve a UE problem to model the route choice behavior at the lower level and as indicated often this is operationalized by a static UE. In most cases, SO NDPs are studied in which accessibility is optimized, where accessibility is expressed as the total travel time in the traffic network and capacity enhancements are the decision variables (Zhang and Lu, 2007; Jeon et al., 2006; Gao et al., 2005; Chen et al., 2006). Different studies incorporated the investment costs within the objective function. Chiou (2005a), Meng et al. (2001) and Xu et al. (2009) optimized total travel time in which the investment was translated in time using a conversion factor. Others translated travel time into cost (Dantzig et al., 1979; Poorzahedy and Turnquist, 1982; Drezner and Wesolowsky, 2003). When elastic demand is considered the objective maximizing consumer surplus is more appropriate than to minimize travel times, because this could be achieved by minimizing demand (Yang and Bell, 1998). NDPs which are also often investigated, are the road pricing problem minimizing congestion or maximizing of revenue (Chen et al., 2003; Viti et al., 2003; Chen and Bernstein, 2004; Chen and Subprasom, 2007; Sumalee et al., 2005; Brands et al., 2009) and minimizing delay in the signal setting problem (Cantarella and Vitetta, 2006; Cantarella et al. 2006; Chiou, 2005b; Sadabadi et al., 2008). Other examples are transit network design problems (Gao et al., 2004) or Taber et al. (1999) in which also land use scenarios were incorporated as decision variables. Although in most cases accessibility is the objective, occasionally other costs, like environmental costs (expressed in money) are added to the travel cost (Cantarella et al., 2006; Mathew and Sharma, 2006) or constraints are added, e.g. related to equity (Meng and Yang, 2002). Aspects like equity and reliability are of increasing interest within NDP research. In Santos et al. (2008) three alternative indicators are proposed for accessibility incorporating equity and these three single objective functions are compared. In Santos et al. (2009) a weighted sum of efficiency, robustness and equity is used as an objective function. Sumalee et al. (2006) used reliability as the objective function by maximizing the probability that the total travel time is less than a certain threshold. Extensions of the NDP are also studied as for example in Kim et al. (2008), Lo and Szeto (2003 and 2009), Szeto and Lo (2008) and Chow and Regan (2011) in which the multi-period NDP is solved, which also incorporates the sequence and scheduling of investments. One other example is extending the NDP with more than one stakeholder at the upper level, with different objectives and different measures available. This is for example studied in Taale (2008) and Ohazulike et al. (2012).

The budget constraints considered are usually on investment costs for road investments. Additionally, technical constraints are considered (e.g. what new connections can be considered). For the road pricing problem mainly technical constraints are formulated for the maximum charge rate and depending on the charging strategy the requirement for a closed cordon. For signal timing control the constraints are also mainly technical in terms of minimum green times and maximum cycle times. However, it is possible to incorporate realizing new DTM measures as a decision variable, although this kind of decision variable has not been found in literature. Additionally, several outcome constraints can be considered which, for example, can be related to equity, revenue or emissions for all types of NDP.

Multiple objectives

There is less research using multiple objective functions at the upper level, although it has been acknowledged that transportation planning is inherently multi-objective in nature (Current and Min, 1986; Current and Marsh, 1993). Because of improved heuristics and increased computer capacities, an increase in research can be found since 2000. In the review of Yang and Bell (1998), which is often referred to in NDP literature, it is also stated that there were only a few authors till then who investigated the MO NDP, although this would be a better approach than simply using a weighted combination. Friesz et al. (1993) is one of the first studies who considered multiple objectives. This research focuses on minimizing the transport costs, construction costs, vehicle miles traveled and dwelling units taken for rights-of-way and used a weighted sum approach in combination with simulated annealing. Taber et al. (1999) considered travel time, per capita cost and land use change as objectives and used a GA to solve this optimization problem. Chen and Subprasom (2007) social welfare maximization (consumer surplus minus costs), profit maximization (revenue minus costs) and minimization of inequality of benefit distribution among road users are considered for the optimal toll problem and solved using a GA. Chen et al. (2010) use travel time and construction costs as two separate objective functions and used an evolutionary algorithm (EA) to solve a capacity enhancement problem. Chen et al., 2003 use maximizing mean profit and minimizing the variance of profit as objectives in the optimal toll and capacity optimization problem subject to demand uncertainty and used a GA to solve this problem. Cantarella and Vitetta (2006) considered travel time, walking time and CO emissions in their optimization using a GA. Yin and Lawphongpanich (2006) also used an EA in combination with a weighted sum approach to optimize the same objectives. Some studies optimize multiple objectives concerning equity and/or robustness (Ukkusuri and Patil, 2009; Sharma et al, 2009; Duthie and Waller, 2008; Santos et al., 2009). Sumalee et al. (2009) optimized road charging design using EAs in which social welfare improvement, revenue generation and equity are considered. In this research these aspects were considered to be an objective or an outcome constraint. When considered as a constraint these were introduced in the objective function through Langrangean multipliers (penalty function). Xu and Chen (2011) consider efficiency, environment and equity as objectives and use a goal programming approach and GA to solve this NDP.

Solutions approaches

For solving the NDP different approaches are possible. As indicated, most problems are formulated as a bi-level optimization problem (Ban et al., 2006). Solving such a problem is normally difficult, because it is non-convex and non-differentiable and has been proven to be NP-hard (Johnson et al., 1978). All studies that did not reformulate the problem therefore use heuristics to solve it. Cantarella et al. (2006) compared various heuristics (hill climbing, simulated annealing, tabu search, GA and path relinking) for a SO NDP and concluded that tabu search and GAs perform best and have higher speed of convergence. Drezner and Wesolowsky (2003) compared heuristics as well, namely a descent algorithm, simulated annealing, tabu search and a GA for a SO NDP, and concluded that the GA performed best. Karoonsoontawong and Waller (2006) compared simulated annealing, GA and random search for the dynamic continuous SO NDP and concluded that GA outperformed the other approaches. Kim et al. (2008) compared simulated annealing and GA for the multi-period SO NDP and concluded that simulated annealing performed best. Xu et al. (2009) compared simulated annealing and GA for the CNDP and concluded that simulated annealing is more efficient, but GA finds better solutions in some cases at the expense of more computation time. Santos et al. (2009) compared the add plus interchange algorithm, variable neighborhood search algorithm and an enhanced GA for a DNDP with elastic demand. The authors concluded that the GA method outperformed the others. Possel et al. (2012) compared GA and simulated annealing for the MO NDP and concluded that GA outperformed the simulated annealing approach.

In most SO NDP research GA is used as solution approach (e.g. Ceylan and Bell, 2005; Chen and Yang, 2004; Chen et al., 2006; Sumalee et al. 2005; Jeon et al. 2006; Guoqiang and Jian, 2007; Santos et al. 2008; Li et al., 2009). However, also other approaches are used. Los and Lardinois (1982) used two hill-climbing techniques to solve the discrete NDP in which multi-starts were used to be able to select the best found local optima. Friesz et al. (1993) used a simulated annealing approach and Poorzahedy and Rouhani (2007) tested several hybrid approaches all based on ant colony search techniques combined with concepts of other heuristics like GA, simulated annealing and tabu search. GAs are also popular solution approaches for the MO NDP. In Cantarella and Vitteta (2006), Chen and Subprason et al. (2007), Chen et al. (2010), Duthie and Waller (2008) Sumalee et al. (2009) and Sharma et al. (2009) a GA is used to solve the MO NDP. Chow and Regan (2011) used the multi-start local metric stochastic radial basis function algorithm to solve a SO NDP. This approach is a heuristic that uses a function approximation method. Solving for constraints can be done in numerous ways. Technical constraints like minimum green times or maximum charge rates are often dealt with in the solution approach by making sure these constraints can not be violated. These kind of solutions are sometimes also possible for budget constraints or outcome constraints (e.g. as a repair action or a smart design). However in most cases some form of Langrangean relaxation is used, which means the constraints are incorporated in the objective function (e.g. Meng and Yang, 2002; Sumalee et al., 2005; Xu et al., 2009).

Reformulating the bi-level optimization problem in a way it can be solved efficiently, is also an active research topic. With reformulating is meant, the adjustment or approximation of the original optimization problem based on additional assumptions. As mentioned before assuming continuous decision variables, even when these are actually not, is an approach used to solve the problem more efficient. Andulaal and Leblanc (1979) for example used continuous investment variables and formulated it as a nonlinear optimization problem. In this research an additional assumption is made that slight changes in capacity does not influence equilibrium traffic flows, which is used within Powell's method and the method by Hooke and Jeeves to solve the problem. Poorzahedy and Turnquist (1982) used an approximation of the original objective function for the DNDP, by replacing minimization of total user cost by the objective function for solving the UE problem (i.e. sum of integrals under the average cost functions). This way solution methods to solve UE problems could be adapted to solve for the DNDP. The reformulated problem was solved using a branch-and-backtrack algorithm. Meng et al. (2001) transferred the bi-level CNDP into a single level continuously differentiable problem using a marginal function tool. The authors prove that this problem remains non-convex, but can be solved by conventional nonlinear differentiable methods. Ban et al. (2006) improved the scalability of the approach of Meng et al., by using decomposition schemes. Dantzig, et al. (1979) introduced a convex formulation assuming system optimal flow patterns for the MNDP, which was solved using a decomposition approach. Patil and Ukkusuri (2007) also formulated the NDP as a single level optimization problem by assuming solving a system optimum assignment at the lower level. This way the problem is easier to solve using nonlinear programming algorithms. Sadabadi et al. (2008) reformulated the problem into a lower bound problem using the system optimal formulation for the lower level problem for which a standard steepest descent method is used. Within Chen and Bernstein (2004), Chiou (2005a), Chiou (2005b), Cho and Lo (1999) the original bi-level optimization CNDP is also converted into a single level standard nonlinear optimization problem by using sensitivity methods to be able to calculate derivatives. These derivatives can be used to linearize the equilibrium constraints. Chiou investigated several CNDPs (toll, signal settings, capacity) and converted these all into single level optimization problems (e.g. Chiou, 2005a; Chiou 2007; Chiou 2008; Chiou 2009). In these studies several solution approaches were used of which almost all were based on gradient methods. Sumalee et al. (2006) reformulated the problem and used sensitivity analysis and a gradient-based optimization algorithm to solve the reliable NDP. Luathep et al. (2011) reformulated the mixed NDP as a piecewise linear programming problem and transformed it into a mixed-integer linear programming problem that was solved using a cutting constraint method. Wang and Lo (2010) used a similar approach for the CNDP. All studies mentioned above are based on a STA at the lower level. There also has been some research on reformulating and solving the NDP in which a DTA is used. Waller and Ziliaskopoulos (2001) reformulated the dynamic CNDP using the system optimal formulation for the lower level to be able to formulate it as a linear program. However, this introduced several limitations that made the approach only useful for limited application. Karoonsoontawong and Waller (2007) provides an overview of these formulations of the dynamic NDP. All of them are based on reformulating the original problem in a linear program and solving it with a standard linear program solver. However, to be able to reformulate the problem, several limitations are introduced. The most important limitation is that the reformulations found for the dynamic NDP are only applicable for single destination networks.

2.2.3 Discussion and conclusions

NDPs have been an active research topic the past few years in which most research has focused on SO NDP. Often the objective is related to accessibility (minimization of total travel time), the decision variables related to capacity enhancements, tolling and signal timing control and the lower level is operationalized by solving the static UE problem. There have been some efforts in incorporating externalities as an objective in the SO NDP as well as the MO NDP. In all cases these efforts were limited to evaluating one externality, namely air quality. However, also other externalities are relevant. The NDPs in which DTM measures are the decision variables are mainly limited to signal control, although more DTM measures are available to optimize the objectives. Recently, operationalizing the lower level by solving the dynamic UE problem is increasing, but still only used in a few studies. As mentioned Janson (1995) found that an approach capturing traffic dynamics provides more flow-consistent solutions than static approaches for the NDP. This is an additional argument for using a DTA model. For solving the NDP, heuristics are used or analytical methods after reformulating the NDP. Using the latter is in general faster in finding reasonable results. Although these methods are of interest, reformulating the original problem generally results in finding less performing solutions. This is also shown in Meng et al. (2001) Chiou (2005a), Luathep et al. (2011) and Ban et al. (2006), in which the simulated annealing approach finds better results in most cases. Most research in which the original NDP was reformulated, concerned turning the bi-level optimization problem into a single optimization problem using additional assumptions. When a DTA is used at the lower level, reformulation is not useful for real cases. In Karoonsoontawong and Waller (2007) it was for example shown that a bi-level formulation is more desirable than single level for the dynamic NDP and bi-level linear program formulations are only formulated for single destinations problems and continuous decision variables. In addition, the optimization problem in this research concerns multiple objectives and solving a dynamic UE problem at the lower level. Solving this problem results in a Pareto optimal set of solutions and requires a higher quality regarding the reformulation in terms of deviations of the original problem. This means that heuristics are needed to solve the MO NDP. In various studies different algorithms are tested and compared. In most cases GA outperformed the other algorithms and GA is also often used in NDP research in which no algorithms are compared. The GA approach has been proven to be capable of solving SO NDP as well as MO NDP, which means GAs can deal with the function types associated with NDP. Although hybrid approaches are proposed to improve the performance in terms of finding better solutions, efforts to accelerate these algorithms in applications of NDP are not found.

Based on these findings the general framework of the dynamic MO NDP should be formed by formulating it as a bi-level optimization problem. The best way to operationalize the lower level is by solving a dynamic UE problem and GA has proved to be a suitable solution approach to solve the system objective functions.

2.3 Concluding remarks

In this chapter extensive background information is provided on DTM and an historical perspective on NDP. This information confirms the problem formulation presented in Chapter 1 and is used in Chapter 4 to formulate the modeling framework and solution approaches presented in Chapter 5. The literature review on DTM shows that the main focus in research is on operational and tactical level, but the application of network approaches is still limited. In almost all cases a single objective related to accessibility is used to optimize mainly traffic signals on a local or corridor level. In practice road management authorities are also searching for appropriate strategies on network level to improve accessibility and livability objectives as well. Research in which livability objectives are considered is limited to local optimization not considering behavioral responses of road users. Research in which the route choice effects are taken into account are focused on the optimal signal setting problem optimizing a single objective related to accessibility in which often STA is used. Research on the optimal signal setting problem shows that if road management authorities anticipate the behavioral response, system performance can increase significantly. The approaches used in practice to formulate strategies, are mainly based on expert judgment in which only a few strategies are considered. Formulating the optimization problem as a NDP is therefore useful.

Research on NDP is extensive. However, most research focuses on single objectives and use STAs to solve the UE problem of the lower level. No research is found in which multiple objectives are optimized and a DTA model is used to solve the UE problem. Actually, there is almost no research in which the lower level is operationalized using a DTA model without reformulating the optimization problem. One possible reason is that STA usually works well for strategic planning and is also used in practice in most cases. However, optimization of DTM measures is often related to congestion problems for specific time-intervals (rush hours) and research has shown that DTA models, also for NDP focusing on capacity expansions, are more appropriate. Second reason is the traditional focus on optimization procedures for single objective optimization problems. Recently, optimization procedures for multi-objective optimization problems are increasing fast. Most important reason is however the computation times needed to solve the dynamic UE problem in combination with heuristics, resulting in computationally expensive procedures. The use of DTA models is also important for the evaluation of the objectives related to externalities. DTM measures influences the use as well as traffic dynamics and can therefore be used to optimize externalities. This will be addressed in Chapter 3, as well as a review on modeling externalities to evaluate these objectives.

Chapter 3

Externalities

Soms moet er iets gebeuren, voor er iets gebeurt
Sometimes something has to happen, before something happens
Johan Cruijff

In Chapter 2 extensive background information is provided on DTM and NDPs. Conclusion of the previous chapters is that DTM measures can be powerful instruments to reduce externalities, but that the state-of-practice of strategic DTM is mainly expert judgment based and research on the simultaneous optimization of the distinguished externalities incorporating traffic dynamics is new. Such research can be helpful for the road management authorities for the deployment of DTM measures. The previous chapters also showed that formulating this optimization problem as a bi-level MO NDP will provide the best possible solutions, because of anticipating the behavioral response of road users. However, it is also shown that this optimization problem is complex and several challenges have to be addressed to perform such an optimization. One of the challenges is to assess the effects of a certain deployment of DTM measures on externalities using DTA models. This chapter provides an introduction on externalities and a review on modeling of externalities using DTA models. This knowledge is used to formulate the resulting general framework in Chapter 4.

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3.1 Introduction

The concept of external effects is widely used in economics, but there is little consensus on the exact definition and interpretation. Verhoef (1994) formulated the following definition: "An external effect exists when an actor's (the receptor's) utility (or profit) function contains a real variable whose actual value depends on the behavior of another actor (the supplier), who does not take these effects of his behavior into account in his decision making process" (p.274). This definition is still somehow vague concerning the extent in which the effects of behavior are taken into account. According to Scasny, Havranek and Melichar (2004) the definition used within the ExternE method, developed by the European Commission to evaluate externalities of energy, is more applicable. This definition is: "The costs and benefits which arise when the social or economic activities of one group of persons have an impact on another group and that impact is not fully accounted for by the first group" (p. 6). This definition is similar to the definition in the policy document on externality research by the European Commission (2003). However, the latter definition excludes externalities for which the second group is compensated for by the first group. That means, independent of the extent in which a person takes the effects of his behavior into account, an external effect can arise. Only when these effects are fully taken into account, or fully compensated by the causing party, these effects are no longer external effects, but direct effects, because it decreases the user benefits.

Table 3.1 Typology of external costs of road transport (adapted from Verhoef, 1994)

	External costs resulting from actual transport activities	**External costs caused by vehicles when not in motion**	**External costs closely related to the existence of infrastructure**
Adverse effects on ecological environments	Air, water and soil pollution Noise pollution Global warming	Pollution caused by production and disposal of vehicles	Severance effects in ecosystems
Adverse effects on social environments	Air, water and soil pollution Noise pollution Accidents Global warming	Use of public space	Visual annoyance, barrier effects
Intra-sectoral effects	Congestion Accidents	Congestion of parking places	

Verhoef (1994) states that there are no significant external benefits of road transport activities and empirical work towards the external effects of road transport can be restricted to external costs. Verhoef also introduced a typology of external costs, shown in Table 3.1. Although there have been discussions about the human factor in global warming, this human influence is acknowledged to be very likely the cause of the observed increase in greenhouse gas concentrations in the first part of the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (2007). In this research global warming is assumed to be part of the external costs resulting from actual transport activities and added in Table 3.1 to the typology of Verhoef.

The MO NDP in this research focuses on the optimization of the use of the traffic system by improving existing facilities. Therefore this study focuses on the external costs resulting form actual transport activities, namely

- Congestion

- Traffic accidents
- Emissions of substances related to air quality (and water and soil pollution)
- Emissions of substances related to global warming (climate)
- Noise

The next section addresses these externalities by presenting some background information and a literature review of methods and models. The examples and data are focused on the Dutch situation.

3.2 Background on externalities

In this paragraph some background information is presented on the externalities congestion, traffic safety, air quality, climate and noise.

3.2.1 Congestion

When the car became more and more popular, cities were not prepared to facilitate this new kind of vehicle. Drastic plans were implemented, consisting of dimming canals and demolishing buildings. The initial belief that the supply of infrastructure needed to meet the growing demand changed, first within cities, later on also concerning highways. This change in belief was also infused by the development that extension of road infrastructure leads to an increase of car use and people moving outside the cities, increasing car use as well. This change in belief was also inflicted by emerging awareness of environmental effects due to traffic and the economic recession in the eighties (Van den Braak, 1996). Opposite of the development of the supply of infrastructure, the demand kept growing more rapidly over years due to increase of population, of possession of drivers license and of cars. In 2007 16.3 million people were living in the Netherlands whereof 12.4 million were older than 20 years. Approximately 10.0 million people have a driver's license and 7.0 million people own a car. In general there has been an enormous increase in number of cars. Between 1960 and 2006 the number of cars in the Netherlands increased from 500,000 cars till approximately 7,200,000 cars. Among other things these developments have led to an increase in the number of vehicle kilometers a year. The estimated current number is 105,531 million kilometers (CBS, 2007). It is expected that between 2000 and 2020 road traffic will increase with 40% (Ministerie VenW, 2004). The total number of travel kilometers (independent of used mode) increased between 1995 and 2005 with 10% up to 184 billion. Approximately 60% of this increase can be explained by growth of population and change in composition of the population. The other 40% is due to changes in individual mobility behavior: increase of distances traveled per person (mainly by women) (KIM, 2007).

Because the supply of infrastructure is not increasing as fast as the demand, congestion occurs, which leads to deteriorating accessibility. In the Netherlands the first problems with accessibility due to congestion emerged in the fifties. These problems however mainly occurred at Sundays due to recreational trips. The first known traffic jam occurred at the interchange Oudenrijn at Pentecost in 1955. After this moment traffic jams became more and more common and nowadays the daily average is 300 km of traffic jams at the Dutch highways. In 2006 it was estimated that there were 41,118 traffic jams and approximately 60 million vehicle loss hours at Dutch highways (Bovag, 2007; AVV, 2004; AVV, 2003). It is estimated that the total amount of vehicle loss hours at the secondary road network is even higher, e.g. network analysis 'Stedendriehoek' (Ecorys, 2006).

The Dutch goals concerning accessibility are formulated in the “Nota Mobiliteit” (Mobility Policy Document) and are about realizing reliable and reduced travel times. The ambition is to reduce the amount of vehicle loss hours at highways in 2020 to the level of 1992, 95% of trips are on time and travel times at rush hours are between cities at the most 1.5 times higher than travel times besides rush hours and on ring roads and other roads at the most 2.0 times higher.

3.2.2 Traffic safety

The objective traffic safety is the actual quantitative safety of a traffic system. It consists out of the actual number of crashes divided into fatal, injured (combined casualties) and material damage only. Factors that influence objective traffic safety are all three traffic system elements, human (e.g. use of alcohol), vehicle (e.g. mass differences between road users) and road (e.g. design and use of road) (SWOV, 2005). The Netherlands has become increasingly safe the past 30 years. Until the 1970’s there was an increase of traffic unsafety as a result of increasing mobility. The past years there is a decreasing trend despite of the increasing mobility and nowadays the Netherlands is one of the safest countries in the world (SWOV, 2007b; Jacobs Consultancy, 2006). In 2006 730 fatalities were registered and it is estimated that the actual figure is 811 (degree of registration of 90%).

Nationally, targets are set to achieve in 2020 (in maximum number of fatalities and in-patients). These targets are a maximum of 500 (originally 580) fatalities and 10.600 in-patients in 2020. Concerning traffic safety, also European legislation influences the national policy. These European directives are mainly focused on safety requirements (EuroNCAP) and requirements of professional chauffeurs. The European Committee has arranged to meet a target of –50% of fatalities for the European Union (EU) as a whole (Ministerie VenW, 2004; Ministerie VenW, 2003; SWOV, 2000; SWOV, 2007a). Measures to meet the national targets are focused at the principles of Sustainable Safety (in Dutch “Duurzaam Veilig”). Road authorities receive funds to invest in safe(r) infrastructure lay out. The central government is focused at influencing behavior of road users, encouragement of innovations in vehicle technology, embedding traffic safety within relevant social sectors, development of instruments for safe transport of goods and associate with health service (Ministerie VenW, 2004).

3.2.3 Climate

There are different substances that are produced as a result of road traffic. Distinction can be made between the substance carbon dioxide (CO_2), which influences the climate, and the substances impairing the air quality. Different chemical compounds like water vapor (H_20), methane (CH_4) and carbon dioxide (CO_2) in the Earth’s atmosphere act as ‘greenhouse gases’. Greenhouse gases absorb the infrared radiation that is reflected by the surface of the earth when sunlight strikes it and therefore retain the heat in the atmosphere. It is estimated that without these gases the mean temperature on earth would be –18 degrees Celsius. Many gases occur in nature and are regulated by numerous processes known as the ‘carbon cycle’. However, due to human activities (called anthropogenic gas concentration) the balance in the existence of these gases in the atmosphere is disturbed and leads to global warming (Augustijn, 1995; MNP, 2006). Carbon dioxide is the most prominent greenhouse gas and the human activities influence mainly this gas by burning fossil fuels. That is why the total amount of greenhouse gases is expressed in carbon dioxide-equivalents reckoning with the differences in global warming potential of the different gases. Traffic and transportation influences the greenhouse gas concentrations by burning fuel. In the Netherlands traffic and transportation is responsible for approximately 20% of the emitted CO_2-equivalents.

Like many other countries the Netherlands signed the agreement concerning the reduction of CO_2-emissions during the climate conference in Kyoto of 1997. The Kyoto Protocol came into force in 2005 after Russia ratified the protocol in 2004. The goal of the Netherlands is to reduce the green house gases in the period 2008-2012 average by 6 percent compared to the year 1990 (Ministerie VROM, 1999; Ministerie VROM, 2005). Shortly after the Kyoto Protocol came into force people were talking about the post-Kyoto Protocol. In the beginning of 2007 the leaders of the 27 EU-countries agreed with a new ambitious climate and energy plan. This plan aims at reducing the energy-use by 20% in the year 2020 compared to the year 1990 (Europees parlement, 2007).

3.2.4 Air quality

The quality of the air is dependent on different substances in the air that may impair the health of nature, including humans. Substances not naturally found in the air or at greater concentrations than usual, are referred to as 'pollutants'. Estimations are made that in the Netherlands 18.000 premature deaths are caused by bad air quality (MNP, 2006). Distinction can be made in stationary sources and mobile sources (mainly traffic) of emissions of pollutants. Traffic can be seen as the main source of emissions. The most important substances that are produced by traffic are nitrogen-oxide (NO_x), nitrogen-dioxide (NO_2), particulate matter (PM_{10}), carbon oxide (CO), sulfur-dioxide (SO_2) and hydrocarbons (HC, e.g. Benzene). As for CO_2 emissions, human activities disturb the balance in the existence of these gases in the atmosphere. Next to the direct emitted substances by traffic (primary pollutants), there are also secondary pollutants that are formed in the air when primary pollutants react or interact. One of them is ozone (O_3) that is one of the important pollutants responsible for photochemical smog (Augustijn, 1995).

The environment regulation is an important aspect of air quality. In the past few years these regulations formed in the Netherlands a major obstacle concerning spatial/infrastructure planning. Different projects are blocked by the Council of State as a result of problems concerning air quality (e.g. realization extra lanes A4 Leiden and realization A74 Venlo – Germany). As is the case for all other European countries, a great deal of the Dutch environment regulation is directly or indirectly determined by the EU as a result of appointed limit values. In the Netherlands there are problems with air quality concerning PM_{10} and NO_2. PM_{10} also called aerosols are particles smaller than 10 micrometer in aerodynamic diameter. A great deal of this substance exists in the air due to natural causes like dust and forest fires. By traffic this particulate matter is generated by burning fossil fuels (mainly gasoline) and abrasion (e.g. of road surface and brake disc) and locally, traffic can be responsible for 20% of the total PM_{10}-concentration. Inhaling PM_{10} can be damaging for your health, next to that it influences the thermal management of the earth and the generation of precipitation and smog. NO_x is a generic term for nitrogen-oxide (NO) and nitrogen-dioxide (NO_2) and is formed by all combustion processes as a result of an endothermic reaction between nitrogen (N_2) and oxygen (O_2) present in the air. A small part is also directly formed by the reaction of fuel with oxygen. NO is relatively unstable and reacts with ozone (O_3) forming NO_2. However, NO is formed by the photochemical reaction of NO_2 (Ganguly and Broderick, 2009; Chang, 1980). Traffic can locally be responsible for 60% of the total NO_2-concentration. Although only high concentrations of NO_2 are damaging health, it is proven that concentrations of NO_2 correlates with health problems. Therefore, its concentration is also used as an indicator for air quality. Next to that, it is an important source for the amount of ozone in the atmosphere, which is harmful, and if NO_2 reacts with water (H_2O) nitric acid (HNO_3) is formed, which is one of the most important elements of acid rain (Augustijn, 1995; Korver et al., 2007). Recently, increasingly attention is paid to dry deposition of nitrogen oxide which influences vegetation.

3.2.5 Noise

Sound is the vibration of matter, as perceived by the sense of hearing. It is created by movement of a source that causes short changes in the matter pressure. The mechanical vibrations, which can be interpreted as sound, can travel through all forms of matter. The matter that supports the sound is called the medium (in this case air). The movements of the vibration of air particles, sound waves, are longitudinal. Sound waves are characterized by the generic properties of waves, which are frequency, wavelength, period, amplitude, intensity, speed, and direction. The speed by which the air pressure changes determines the pitch and is described by the frequency, which is the amount of vibrations per unit of time (Hertz, 1 Hz is one vibration per second). For humans, hearing is limited to frequencies between about 20 Hz and 20000 Hz, with the upper limit generally decreasing with age. The deviation of the average pressure is called the sound pressure (p). De size of the pressure change is described by the amplitude of the wave, which is the maximum pressure difference in relation to the average, or equilibrium, pressure. The sound intensity is defined as amount of energy per second per unit area (Watt/M^2). The sound pressure level (SPL) or sound level is expressed based on the logarithm of effective sound pressure (reference level is based on the hearing threshold at 1000 Hz) resulting in the amount of decibels. This SPL can also be calculated by using sound intensity. This SPL is useful, because the ear is capable of detecting a very large range of sound pressures. The ratio of the sound pressure that causes permanent damage from short exposure to the limit that (undamaged) ears can hear is above a million. Next to that, the sensitivity of the human ear is little sensitive for little changes in sound intensity and this measure better approaches the way loudness is experienced by humans (Augustijn, 1995; Robertson et al., 1998; Waterman, 2008 en Universiteit Gent, year unknown). It is also known that the human hearing system is more sensitive to some frequencies than others. In 1924 Fletcher and Munson found a relation between frequency and loudness. This and different other studies resulted in an equal-loudness contour recorded in the international standard ISO 226:2003, which is a measure of sound pressure level over the frequency spectrum. The lowest equal-loudness contour represents the quietest audible tone and is also known as the absolute threshold of hearing. The highest contour is the threshold of pain. The unit of measurement for loudness levels is the phon. By definition, 1 phon is equal to 1 dB SPL at a frequency of 1 kHz. Because not loudness but sound pressure is measured, frequency weighting is used to determine the loudness level. A-frequency-weighting is the most commonly used of a family of curves originally defined in the International standard IEC123 and various national standards relating to the measurement of sound level, as opposed to actual sound intensity. The A-weighting is based on the 40 phon equal-loudness contour and results in the sound level dB(A). Because sounds vary over time there are different ways to express sound levels. Often the equivalent sound level is used or variants of this measure (Augustijn, 1995; Robertson et al., 1998; Goodman, 2001; Waterman, 2008 and Universiteit Gent, year unknown).

Noise pollution (or environmental noise) is displeasing human or machine created sound that disrupts the activity or happiness of human or animal life. Noise pollution and resulting annoyance deals in considerable extent with perception and differs per person. However there are certain levels of loudness that can be damaging health (e.g. by damaging sense of hearing or disturbing ones night’s rest). There are also indications that noise has damaging health effects concerning cardiovascular diseases and high blood pressure and noise can lead to diminishing reading skills by school children. (Robertson et al., 1998; KIM, 2007; Van Kempen et al., 2002; Van Kempen et al. 2005; CE, 2007).

The most annoying source of noise in the Netherlands is road traffic. In 2003 29% of the Dutch population aged 16 years and older indicated to be severely annoyed by this type of noise. (Universiteit Gent, year unknown; KIM, 2007). Also in EU it is estimated that in 2003 up to 30% of the people were highly annoyed and given the rapid urbanization, noise annoyance might increase among urban population in both developed and developing countries. (Jakovljevic et al., 2009). Noise is produced by road traffic as a result of two main factors. Propulsion noise and tire/road noise (rolling noise). A third factor aerodynamic noise is often combined with tire/road noise. At low speeds the sound of the engine dominates and at high speeds rolling noise (boundary is around 40 km/h for passenger cars dependent on road surface and higher for trucks) As for air quality Dutch regulation is directly or indirectly determined by the EU (Peeters, 2007; Robertson et al., 1998; FHWA, 1996).

3.3 Modeling externalities

For the assessment of externalities, often output of STA models is used in combination with externality models, also called effect models. These effect models usually consider link loads at the 24-hours level. The emission of pollutants is, for example, determined by multiplying the number of vehicle kilometers (output of the traffic assignment model) and emission factors expressed in gram/km (TNO, 2005; Smit, 2006). Due to the rapidly increasing possibilities of using DTA models on large scale transportation networks, several models have been developed to assess externalities in a dynamic context. Figure 3.1 provides a general framework for modeling externalities using the output of traffic assignment models.

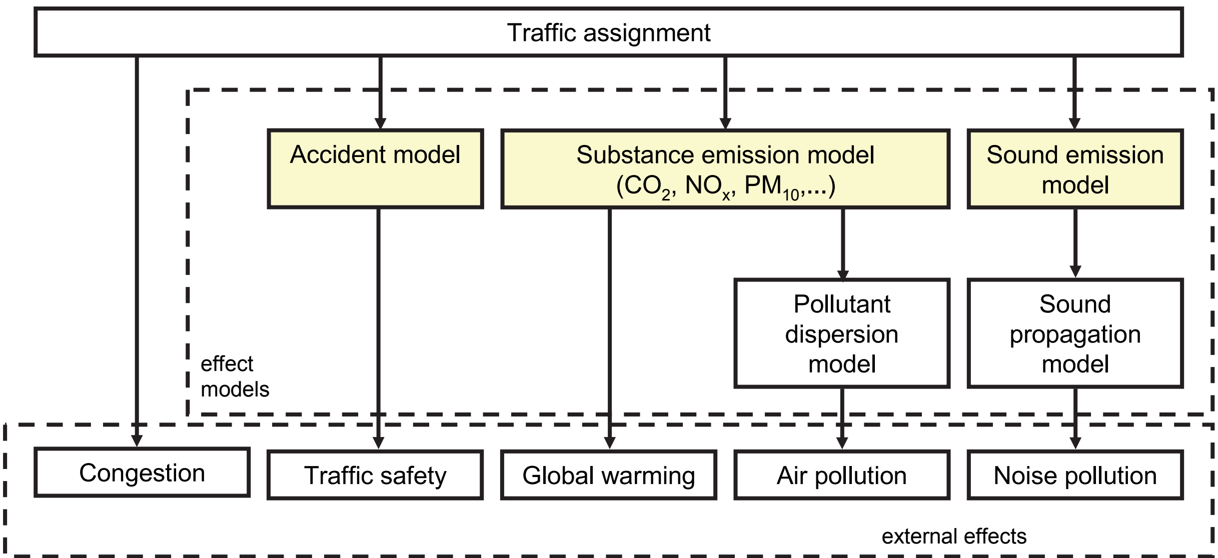

Figure 3.1 General framework for modeling externalities using traffic assignment models

Different studies have shown that there is a proven relation between the traffic dynamics and externalities. High speeds, significant speed differences between vehicles, and speed variation (accelerating, braking) have for instance a negative effect on traffic safety and emissions of pollutants (Rakha and Ahn, 2003; Aarts and Van Schagen, 2006; Beek et al., 2007; Barth and Boriboonsomsin, 2008; Can et al., 2009). The emission of carbon dioxide is directly proportional with the fuel consumption and therefore dependent on the driving speed of vehicles and the level of service of traffic streams (Wismans, 2007). Barth and Boriboonsomsin (2007) also state that comparative to source measures, like alternative fuels and improving efficiency, little attention is given to CO_2 emission associated with traffic congestion. Improved traffic operations can result in short-term CO_2 reductions, because it is commonly known that traffic congestion increases CO_2 emissions.

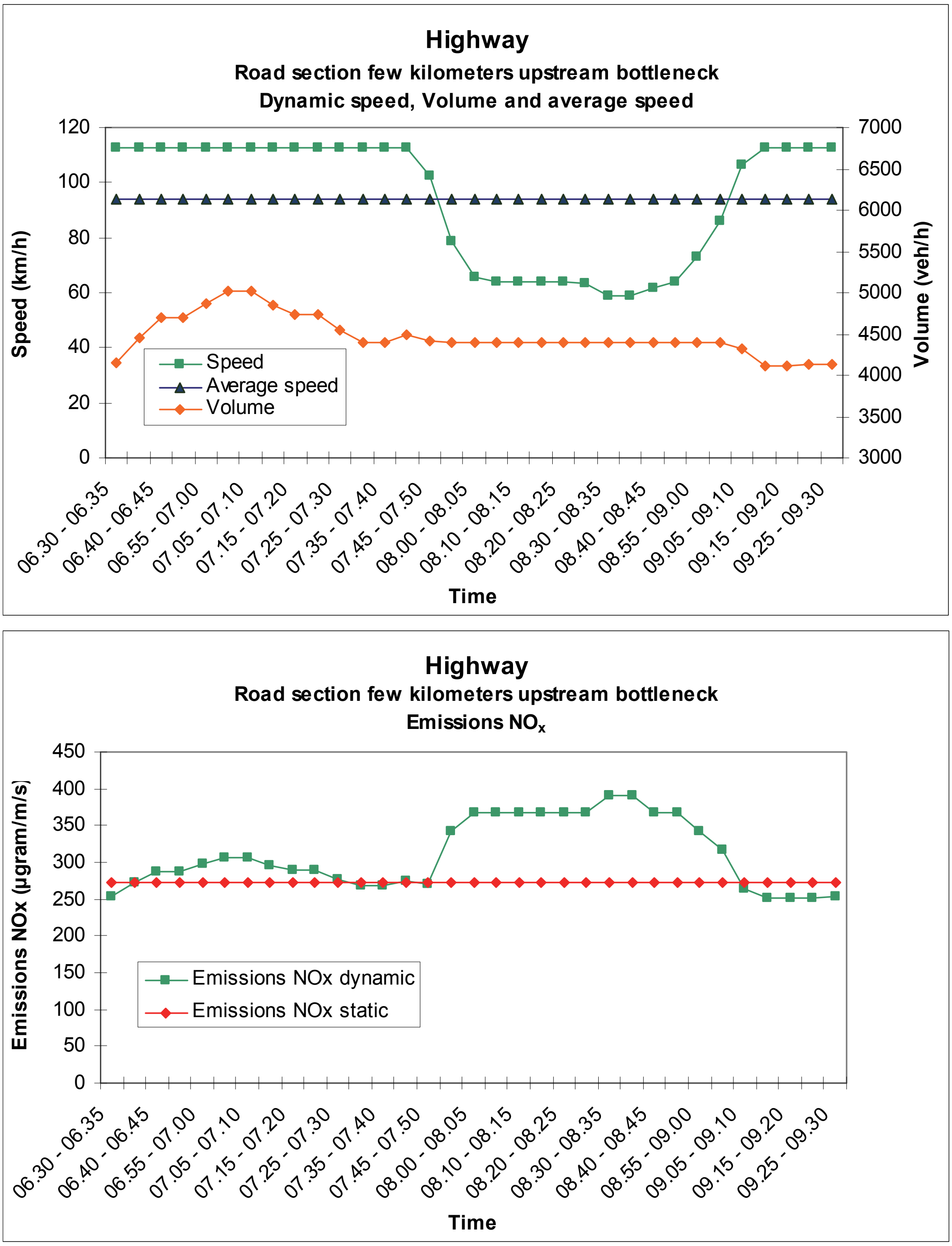

Figure 3.2 Example of influence traffic dynamics on emissions (Wismans et al., 2011)

The emissions and concentration of NO_x and PM_{10} by traffic is dependent on many different factors. The driving cycle, which depends on speed, acceleration/deceleration and level of service, is, next to individual driving behavior and mechanical characteristics of vehicles, an important explanatory variable for emissions. Traffic dynamics are therefore important explanatory variables for emissions, but also relevant for the concentrations. Gram (1996) found that traffic emission calculations should be based upon counts or simulations of both hourly traffic composition and driving conditions and that it may lead to errors in the description of local air quality if the dispersion calculations are based upon emissions from annual average daily traffic, scaled according to average traffic intensity variations. Noise is dependent on vehicle speeds and speed variation and therefore of traffic flow dynamics (Augustijn, 1995). Research shows that the relation between the logarithm of speed is linear with sound pressure level (in dB(A)) (Peeters, 2005, FHWA, 1996). This means that the effect assessment of external effects can be improved by using temporal information about flows, speeds and densities, which is output of DTA models. Figure 3.2 shows for example the influence of traffic dynamics on the NO_x emissions on a road section streamupward a bottleneck, by comparing the emissions based on average demand and speed with emissions based on temporal information.

However, there are additional reasons to use the output of DTA models instead of STA models. The limitations of STA particular for over-saturated traffic conditions are widely recognized. STA models predict congestion on wrong locations, namely downstream the bottleneck instead of upstream, do not model spillback and do not take into account that bottlenecks will influence downstream travel demand. DTA models are therefore also better suitable to model over-saturated traffic conditions in general. However, these limitations also influence the assessment of externalities using STA models. To investigate the consequences, a comparison is carried out on a highly congested highway corridor, namely the A12 between Gouda and The Hague in the Netherlands. In this comparison for the morning rush hour a traditional STA model using travel time functions and the Streamline macroscopic DTA model are used. For the highway network, also measured flow and speeds (using detector data) are available for all highway links of the morning peak. Note that these measurements were not used to calibrate the model. Network and demand were derived from an existing model of the region (i.e. Spitsmijden model, base year 2006, (Van Amelsfort et al., 2008)). Figure 3.3 shows the average outcome for the morning rush hour in loads (bandwidth) and speed ratio (average speed/free speed) of the measurements, STA and DTA. The total demand in both models is the same during the rush hour, however in the DTA model a dynamic OD matrix was used. The results show that the DTA model provides more realistic flows and speeds, based on the comparison with measurements, than the STA model.

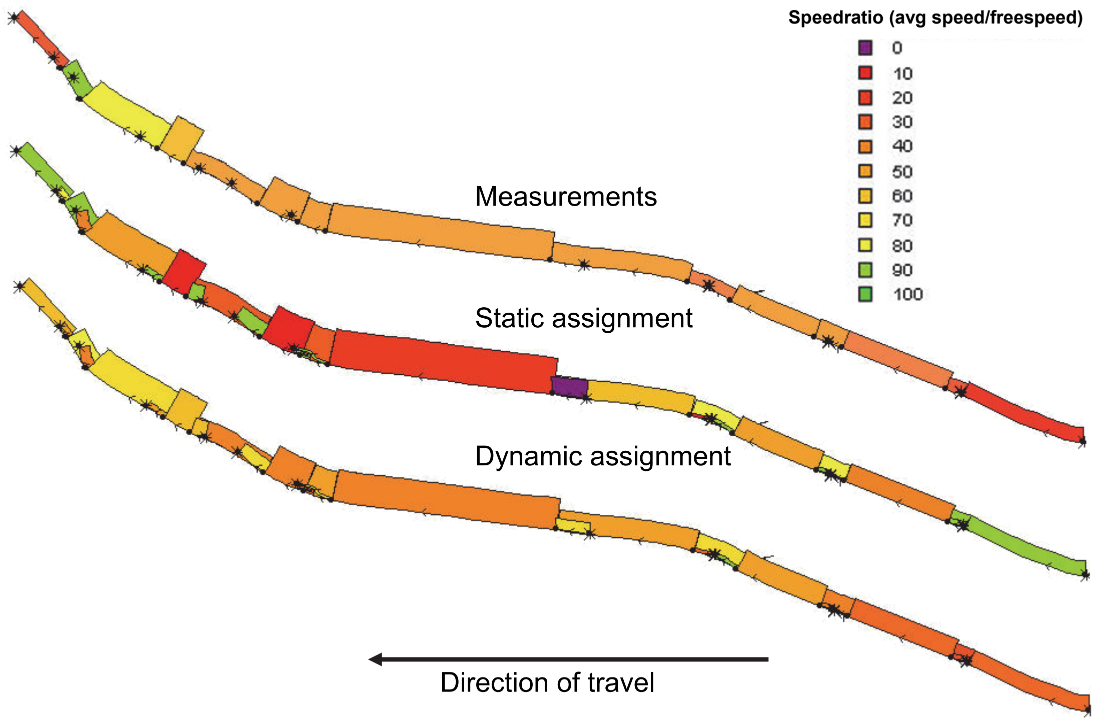

Figure 3.3 Results A12, Gouda –The Hague (Wismans and Van den Brink, 2012)

Both models, as well as the measured volumes and speeds, were connected with the ARTEMIS model (emission of substances) and AR-INTERIM-CM model (emission of sound) to determine the influence on emission. These methods will be described in Chapter 4. Because the differences between STA, measurements and DTA in emissions comprises the difference in loads and traffic dynamics, the total emissions of substances were also corrected for the differences in total loads per link. This means that for the corrected effects the weighted average emission factors are calculated.

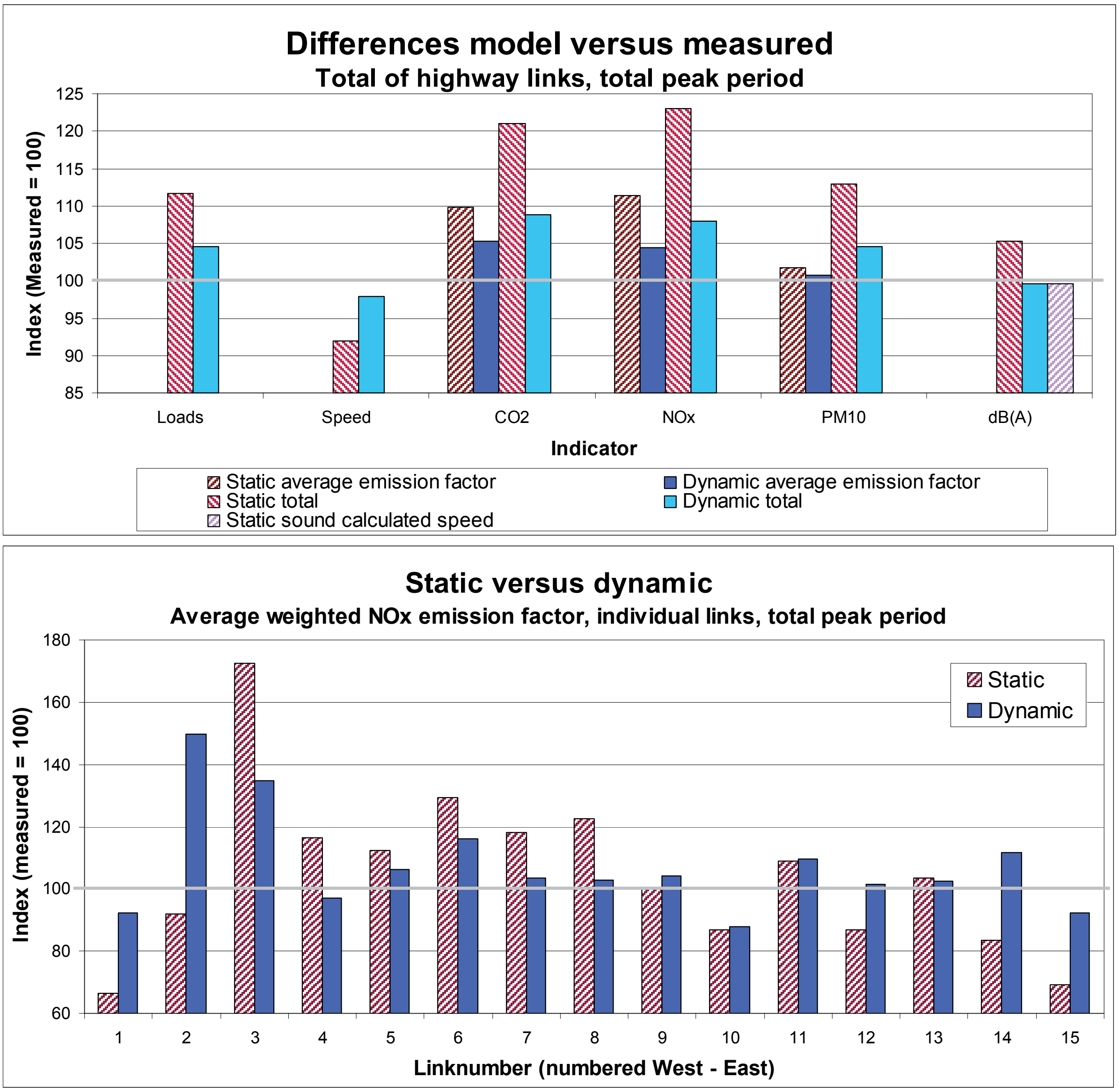

Figure 3.4 Results assignments on emissions A12, Gouda –The Hague (Wismans and Van den Brink, 2012)

Figure 3.4 shows the results for the total of the highway links, and for NO_x for the individual highway links (corrected and not corrected). The emissions based on the measurements are the reference case (i.e. measurements = 100), which means that if the value is closer to 100, the estimated emission based on the model is closer to the measurements. For sound two comparisons are presented. The index 'static total' shows the difference in average sound power level when the static emission calculations are based on the speed limit (which is current practice when STA are used) and the index 'static sound calculated speed' shows the difference when the calculated speed, based on the travel time functions, is used. The results show that the emissions are significantly different when traffic dynamics are taken into account and the DTA model is better capable in reproducing the emissions based on the measurements. The differences between STA and DTA are also relevant for the assessment of possible measures. When assessing the effects of an additional lane realized between Zoetermeer and Nootdorp, the STA model predicts a reduction of all emissions of substances and only changes in emissions on the links where the additional lane is realized. The DTA model predicts changes in emissions on almost all links, because interactions are taken into account, which can even results in an increase in emissions on network level. In Wismans and Van den Brink (2012) the complete comparison is presented. This knowledge also emphasizes the need for using the output of DTA models to determine the externalities, instead of using the output from STA models (Gram, 1996; Golob, Recker and Alvarez, 2004; Lord, Manar and Vizioli, 2005). The next sections discuss the modeling of externalities using the output of DTA models.

3.4 Modeling congestion

In general, the externality congestion comprises the fact that road users have an influence on the travel times of other road users, which they neglect in their decision. Within research on congestion pricing, the externality congestion is often translated to congestion costs and combined with the effect of congestion at other costs like fuel costs, environmental pollution and traffic accidents (for example by Qingyu et al. (2007) and Verhoef and Rouwendaal (2004)). In this research the external effects of traffic are treated separately. The externality congestion is directly related to the objective accessibility, which is traditionally used as an objective for the deployment of DTM measures. However, improving accessibility by implementing a measure, can be the result of reducing congestion problems, but also reducing free flow travel times. In this research minimizing congestion and maximizing accessibility are considered as one objective, operationalized by optimizing efficiency. The concept of optimizing efficiency on a network level is closely related to the traditional comparison between the UE and the system optimum, which have been extensively studied in the literature (Prashkar and Bekhor, 2000). For more background information about this subject Sheffi (1985) is recommended. Important input for indicators related to congestion and accessibility are the travel costs. To assess the effects of measures at travel costs, traffic assignment models are used as earlier described, which is a direct outcome of these models.

Within STA models link cost functions are used to determine the link cost dependent on the link load, which are used to assess total travel costs. Nie et al. (2004) state that most link cost functions including the well known BPR travel cost functions (US bureau of Public Roads, 1964) are polynomials whose degree and coefficients are specified from statistical analysis of real data and can be used to assess the travel costs. Within Smit (2006) an overview is given of other travel cost functions. DTA models directly compute the travel costs in terms of travel times, often based on simulating traffic flows (i.e. macroscopic DNL) or car following behavior (i.e. microscopic simulation). Already in 1978, Dewees used a traffic simulation program to estimate the number of vehicle hours of delay and demonstrated that traffic simulation programs for estimating congestion costs are useful, which is a logical conclusion.

3.5 Modeling traffic safety

In general, the accepted indicator for traffic safety is the number of accidents per type (e.g. fatalities and injuries). However, in traffic models typically no accidents occur. In Morsink et al. (2008) it is stated that modeling of actual accidents is not useful in the current traffic models as a result of the numerous factors influencing the probability of an accident occurrence. Furthermore, these accident occurrences are sporadic and random in nature. Therefore, it is complex to estimate accidents in terms of time and place for specific circumstances, which can be modeled within a traffic model. However, there are some efforts to model accidents or near-accidents within microscopic dynamic traffic models. For instance, in Archer (2001) cognitive models are connected to incorporate possible errors of drivers.

3.5.1 Model types

To assess effects on traffic safety, accident risk based models (ARBM), accident prediction models (APM) or safety performance indicators (SPI) can be used. ARBMs are descriptive models and based on traffic accident data and exposure data. APMs, also called safety performance functions (SPF) or crash prediction models (CPM), are based on available data to quantify the relation between accidents and quantities that describe infrastructure use (e.g. speed, or flow) and characteristics. An SPI, also called surrogate measures, describes the quality of traffic safety of a traffic system and is similar to an APM. Both use the same indicators, because these have an (expected) causal relationship with accidents. The difference is that an SPI not necessarily results in numbers of accidents, but for example explanatory variables like time-to-collision (TTC) (Morsink et al., 2008). Table 3.3 shows the main characteristics of these model types.

To asses the effect of measures on traffic safety using traffic models, the most common method is to use ARBMs that are based on the relation between exposure and accidents. Risk is the number of accidents divided by exposure. Exposure in this case is the number of vehicle kilometers or traffic flow and risk is the number of accidents per vehicle kilometer, possibly differentiated by road type or estimated as a function of flow. These models represent a useful instrument for descriptive and comparative traffic safety analysis (Archer, 2005). However, this method is often also used in combination with STA models and sometimes used in combination with DTA models to predict changes in number of accidents as a result of measures taken (Lord, 2001; Dijkstra et al., 2008).

In general, an APM is a mathematical equation that expresses the average accident frequency as a function of traffic flow and other road characteristics. However, most common models use the annual average daily traffic (AADT) level as the only input. Because of the discrete, non-negative nature of accident count data and the reality that the variance in the number of accidents increases as the traffic flow increases, traditional least squares regression models are not used. It is more common to apply maximum likelihood methods that are referred to as generalized linear models (Lord and Persaud, 2000; Archer, 2005). One of the earliest works in which this approach is used was Maycock and Hall (1984).

For road links a the number of accidents can be described by a power function of the flow and is the basic form of nearly all modern APMs (e.g. Greibe, 2003; Lord et al., 2005; Reurings et al., 2006):

$$\text{number of accidents}_a = \alpha V_a^{\beta}, \quad \text{or} \quad \text{number of accidents}_a = \alpha V_a^{\beta} \exp\left(\sum_j \gamma_j x_{j_a}\right) \tag{3.1}$$

where V is the AADT. Parameters α, β and γ depend on the road geometry and environment. The second formula is used when more explanatory variables x related to road characteristics are used. When enough data is available, it is more favorable to separate the data in different categories than create one model with many explanatory variables, since models with many variables are inflexible (Hauer and Persaud, 1996). Most studies found that the number of accidents usually increases at a diminishing rate as traffic flow increases, which means that $\beta < 1$. Lord and Persaud (2004) and Lord et al. (2005) also use this relation for road links, but included the link length (ℓ) as an explanatory variable. This was earlier proposed by Mountain et al. (1996) to account for minor intersections for which no traffic counts are available at road sections (N is number of intersections on road section):

$$\text{number of accidents}_a = \alpha \ell_a^{\beta_0} V_a^{\beta_1}, \quad \text{or} \quad \text{number of accidents}_a = \alpha \ell_a^{\beta_0} V_a^{\beta_1} \exp\left(\delta N_a\right) \qquad (3.2)$$

For intersections b the basic used relation is given by (see Maycock and Hall, 1984; Lord and Persaud, 2004; Rencelj, 2009):

$$\text{number of accidents}_b = \alpha V_{1_b}^{\beta_1} V_{2_b}^{\beta_2}, \quad \text{or}$$

$$\text{number of accidents}_b = \alpha V_{1_b}^{\beta_1} V_{2_b}^{\beta_2} \exp\left(\sum_j \gamma_j x_{j_b}\right) \qquad (3.3)$$

where α, β and γ are parameters specific to the intersection type, posted speed limit and location, and V_1 and V_2 represent the primary and secondary traffic volumes (AADT). The primary traffic volumes are the entering flows on the major roads and the secondary traffic volumes the entering flows on the minor roads. The second formula is used when more explanatory variables x related to intersection characteristics are used. This basic form is also often used to describe the relation between accidents and different road users (e.g. passenger cars and pedestrians). Hiselius (2004) for example used this formula to investigate the influence of heavy goods vehicles (HGVs).

There are various studies that have estimated APMs based on volumes for 24-hours for specific situations (e.g. Persaud and Nguyen, 1998; Lord, 2002; Greibe, 2003). Most variants try to include more explanatory variables into the model. For example, in Greibe (2003) the speed limit, road width, number of exits per km, number of minor side roads per km, parking and land use are included. Within Dijkstra (1998) and Reurings and Janssen (2007), many of these APMs are described for rural and urban roads. While most APMs are based on the relationship with daily traffic volumes, there are also some models based on hourly volumes, speeds, densities and volume/capacity-ratios (Solomon, 1964; Nilsson, 1981; Garber and Gadiraju, 1989; Finch et al., 1994; Martin, 2002; Hiselius, 2004; Lord et al., 2005).

The sporadic nature of accidents and traffic data availability at urban roads results in difficulties to collect enough and good information to estimate an APM. That is one of the reasons why also SPIs are used to assess the effects on traffic safety. The most prevalent literature in SPI is related to traffic conflict techniques (Glauz and Migletz, 1980). The past few years a lot of research has been conducted to assess the effects on traffic safety using dynamic models and microscopic simulation models in particular. An advantage of these models is the large amount of detailed information concerning level of service and interaction between vehicles and vehicle status like driving speed. However, also within microscopic dynamic traffic models no accidents occur. SPIs can be used to measure the spatial and/or temporal proximity of safety critical events and are assumed to have an established relationship with accidents. In the past years, many surrogate measures, also called proximal measures, have been developed. By focusing on measures of the quantity and the quality of road-user behavior and interaction, an indication of prevailing traffic safety levels can be obtained. In Archer (2001) and Eisele and Toycen (2005) it is emphasized that the use of these surrogate measures offer also advantages related to empirical research, because these situations occur more frequently, also in real traffic. Therefore, shorter periods of monitoring are sufficient. They are also adaptive to the specific characteristics and conditions of particular traffic locations or facilities, making them useful in before-and-after study designs, and other safety assessment strategies. Most surrogate measures have been developed to be used in combination with microscopic DTA models and are related to traffic conflicts. The primary conflict severity measure that has been proposed is the time to collision (TTC) (Hyden, 1987). Other examples are post encroachment time (PET), potential collision energy (PCE) at a microscopic level, and shock wave frequency, delay and queue length at a more aggregate level. An extensive overview of surrogate measures can be found in Archer (2005) and FHWA (2003).

3.5.2 Application

ARBMs are often used in combination with STA models and sometimes also DTA models to assess traffic safety. Zantema et al. (2008) used for example the macroscopic DTA model INDY in conjunction with ARBMs to asses the effects of Pay-As-You-Drive on traffic safety.

Al-Deek et al. (1993) is one of the first to estimate an APM in combination with traffic models. In this research different accident risk factors for freeway and arterial roads, high and low volumes, congested and uncongested traffic situations were estimated. These sixteen different accident risk factors can be used in combination with DTA models to estimate the impact of advanced traffic information systems (ATIS) on accident rates. Unfortunately, the authors did not provide a comprehensive description of the various APMs and risk factors and did not apply their method. Lord and Persaud (2004) is one of the rare studies found that actually applied APMs in combination with traffic models. They used the STA model EMME/2 and microscopic DTA model PARAMICS and combined three APMs all based on the relation between volume (AADT) and accidents for nodes, links and link intersections to estimate the number of accidents. Chatterjee and McDonald (1999) used an APM based on AADT in combination with the mesoscopic DTA model CONTRAM to determine the network safety effects of dynamic route guidance. Within this research the AADT was estimated using the output in the afternoon peak. Look (2001) also investigated the network safety effects of dynamic route guidance using PARAMICS integrated with a set of APMs for links and intersections. The APMs used were based on hourly traffic volumes for intersections (five different APMs dependent on traffic streams turning left or right and through traffic) and an APM based on AADT for links.

There are numerous examples of SPIs used to assess traffic safety in conjunction with traffic models. Malone et al. (2003) used MIXIC and applied TTC and shockwaves to study the effects of vehicle-vehicle communication. Yannis et al. (2003) used SIMONE and SISTM and applied TTC to investigate the effects of advanced cruise control. VISSIM was used by Eisele and Toycen (2005) and they used TTC to determine the effects of access management.

3.5.3 Discussion

ARBMs are often used to assess traffic safety. These models assume that the individual probability of being involved in a traffic accident increases linearly as exposure increases. However, different studies, e.g. Lord (2002), show that the relationship between accidents and exposure is frequently nonlinear, in which the number of accidents usually exhibits diminishing increases as traffic flow increases. Because of this nonlinearity, most safety research focuses on APMs (Lord, 2001; Sawalha and Sayed, 2005).

Most studies have estimated APMs based on AADT volumes for specific situations and some tried to include more explanatory variables into the model. However, Lord et al. (2005) state that little attention has been paid to the relationships of vehicle density, level of service (LOS), vehicle occupancy, volume/capacity (V/C) ratio and speed distribution. Despite overall progress, there is still no clear understanding about the effects of different traffic flow characteristics on safety. All known research trying to estimate APMs incorporating traffic dynamics is based on data of highways. Most of them are based on uncongested flow conditions, while Brownfield et al. (2003) found a number of statistical significant changes in accident rate as result of congestion. In Archer (2005) it is also stated that many models suffer from a lack of flexibility and lack a sound theoretical foundation, thereby restricting the predictive ability and the possibilities for generalization. In addition, Sawalha and Sayed (2005) showed that recalibration of an APM is absolutely necessary before transferring them for use in different time periods and spatial regions. Although it is recognized that traffic dynamics are an important explanatory variable to predict accidents, still little APMs are found in the literature that include such variables, especially for urban road networks. Important reasons are the facts that accidents occur sporadic and that traffic data at urban roads is largely unavailable, which results in difficulties to collect sufficient and good information to estimate APMs. This is also why SPIs are used to assess the effects on traffic safety. However, these surrogate measures only incorporate some elements of the explanatory variables (single vehicle crashes are for instance not incorporated in conflict based measures). These methods also rely on accurate modeling of vehicle interactions, which highly depends on the validation and calibration of the vehicle models at this level. In addition, to be able to use these measures, a statistically reliable causal relationship with accidents is necessary, which is subject of various studies (Gettman and Pu, 2006; FHWA, 2008). These studies show a correlation for urban signalized intersections, however FHWA (2008) showed that the traditional (volume-based) APMs are better correlated.

It can be stated that there is still a gap in knowledge to assess traffic safety with traffic models in general and DTA models in particular. Most research is related to the use of microscopic DTA models in conjunction with SPIs. For now only ARBMs or APMs at the aggregate level (24 hour level) can be used in conjunction with macroscopic DTA models.

3.6 Modeling emissions

The indicator for the effect of traffic related to global warming is the total amount of CO_2 emitted by traffic. To assess the effects concerning air quality it is, in contrast to global warming, of interest to know the concentration of substances like NO_2 and PM_{10} at certain locations, also because there are regulations concerning limit values of these concentrations. The computation of the concentration of substances is done in two steps. The first step is the computation of the amount of emissions, the second step is the computation of the dispersion of these substances. Traffic models are generally used to deliver input needed to calculate the amount of emissions at certain locations. That is why this section focuses on emission models. Dispersion models depend among others on the wind direction and wind speed and are beyond the scope of this research.

3.6.1 Model types

There are many factors that influence the amount of emission. In general, these are at the vehicle level, i.e. vehicle characteristics and car driver behavior (possibly influenced by the traffic situation). At the road section level, these are traffic volume, road design, composition of car park and flow circulation (Smit, 2006; Pandian et al., 2009). To determine emissions on road links a the next general formula is used:

$$\text{emission of substance}_a = E\ell_a V_a, \tag{3.4}$$

where E is the emission factor and $\ell_a V_a$ the number of vehicle kilometers. This method is generally used in conjunction with traffic models. The factors that are determinative are averaged or used to differentiate the emission factors and vehicle kilometers. Because DTA models also calculate the level of service, emission factors can be further differentiated using speed-dependent emission factors or more comprehensive emission models. The CO_2 emissions of vehicles are directly proportional with the fuel consumption. Both methods, directly calculating the CO_2 emissions or fuel consumption, can therefore be used to assess the effects on CO_2. Although sometimes also the emissions of other substances like NO_2 and PM_{10} are derived from the fuel consumption, these emissions are not directly proportional.

There are many different emission models that can be connected to traffic models to assess the effects on air-quality. The types and main characteristics that can be distinguished are presented in Table 3.3 (Hickman, 1999; Joumard, 1999; Boongrapue et al., 2005; Boultier et al., 2007; EC-METI Task Force, 2009). The earliest work on emission models focused on modal models in which the effects of different operating modes were explicitly simulated (e.g. Kunselman et al., 1974).

Aggregated emission functions use single emission factors representing a particular vehicle type and a general driving type. Vehicle operation is therefore only taken into account at a very rudimentary level. More sophisticated aggregated emission functions are based on traffic conditions in which cycle average emission rates are correlated with various driving cycle parameters and are referenced to specific traffic situations. These traffic situations relate to certain conditions (e.g. level of service). Average speed models are based upon the principle that average emission factors vary according to the average speed during a trip. In general a continuous average-speed emission function is fitted for several vehicles over a range of driving cycles. In principle, the input is the trip-based average speed, although in practice it is also common for local speed measurements taken at discrete locations to be used. Within regression models, each driving cycle used is characterized by a (large) number of descriptive parameters (e.g. average speed, relative positive acceleration and number of stops per km) and their derivatives. A regression model is fitted to the average emission values over the various driving cycles, resulting in the determination of the best predictors for emissions. In modal models, emission factors are allocated to the specific modes of vehicle operation encountered during a trip. Different types of modal models exist, and the terminology used can be confusing. A possible simple type defines vehicle operation in terms of modes like ‘idle’, ‘acceleration’, ‘deceleration’ and ‘cruise’. Instantaneous speed based models relate fuel consumption and/or emissions to vehicle speed and acceleration during a driving cycle, typically at one-second intervals. Instantaneous power based models use a description of the engine power requirement in which the most complex models represent physical and chemical phenomena that generate emissions. Methods part of these types are load based using engine maps or methods using a surrogate of engine power by using e.g. the product of speed and acceleration instead of acceleration, and relate fuel consumption and/or emissions to vehicle speed and this product.

There are two basic types of emission models, one based on bag measurements and the other on instantaneous measurements. Within bag measurements, the total exhaust emissions are collected in a sample bag and analyzed after completion of the driving cycle. This approach is until recently the dominant approach in emission model development. In instantaneous measurements the exhaust emissions are measured continuously. The instantaneous measurement method is becoming increasingly common for environmental emission factor calculations and engine development. However, there are some additional aspects such as the correction for the time lag in the dynamics of gas transport, sampling and analysis system. While models based on bag measurements possibly allow interpolation for nonmeasured cycles, instantaneous models also make it possible to predict emissions for different vehicle loads, slopes or gearshift scenarios (Ajtay et al., 2005).

Important aspects of emission modeling are hot emissions, cold emissions and evaporation losses. Evaporation losses of gasoline are in general due to breathing losses through the tank vent and fuel permeation during driving and parking. Hot emissions are the emissions of substances by thermally stabilized engine operation and cold emissions are the emissions during the warming-up phase (Hickman, 1999). All emission models predict hot emissions, but only few explicitly or implicitly predict cold start and evaporative emissions (Smit, 2006). Cold emission rates are usually accounted for by using an excess emission over the hot emission rate (NedjadKoorki et al., 2008). Within the COPERT model (Ntziachristos and Samaras, 2000) for example, the cold emissions are calculated as excess emissions per km, within the ARTEMIS model (INFRAS, 2007) they can be calculated per start and as excess emissions per km, within the MOBILE model (EPA, 2003) the cold emissions are estimated per start, and within the CAR model (Infomil, 2007) the emission factors are already compositions of hot and cold emissions. Next to hot and cold emissions, emission models can also use (other) factors for hot emissions in order to correct for deviations of the standard conditions, such as gradient, load, mileage (age of vehicle) and temperature. Next to hot, cold and evaporation losses, traffic produces also non exhaust emissions of particulate matter (PM) as a result of brakes abrasion, tire wear, and pavement erosion. Probably because these emissions are non-regulated, few emission models take these emissions into account. Exceptions found are COPERT and CAR.

3.6.2 Application

In combination with STA models, aggregated emission functions or average speed based models are generally used to assess the effects on emissions (e.g. Sbayti et al., 2002). Several DTA models have or have been used in conjunction with emission models, particularly microscopic models. DTA models can capture the effect of traffic variations, which means that combining dynamic models with emission models, improvements can be made in assessing the emissions. Most applied methods are based on an average speed approach, a driving mode approach (modal models), or an instantaneous speed based or power based approach. Applications are numerous. The microscopic DTA model INTEGRATION has an emission module called VT-micro, which has been developed as a regression model from experimentation with numerous polynomial combinations of speed and acceleration and is applied on an instantaneous basis (Rakha et al., 2004, Ahn and Rakha, 2008). The mesoscopic roundabout traffic model aaSIDRA incorporated an emission model using a modal approach to evaluate the emissions and the microscopic model aaMotion uses an instantaneous speed based emission model (Akcelik and Besley, 2003). Coelho et al. (2006) developed three different instantaneous speed based emission functions for three different speed profiles (‘no stop’, ‘stop once’, and ‘stop more than once’) and integrated this into one emission model to estimate emissions using the aaSIDRA traffic model for the evaluation of roundabouts. Kun and Lei (2007) used the microscopic model VISSIM and the load based emission model CMEM for the evaluation of traffic control strategies. Huang et al. (2009) used VISSIM in combination with QUARTET, which is an average speed based emission model and MODEM, which is an instantaneous speed based emission model to study the effects of road maintenance works on emissions. Int Panis et al. (2006) developed an instantaneous speed based emission model and used it combined with the microscopic model DRACULA to study the influence of traffic speed limits at emissions. Mensink and Cosemans (2008) estimated instantaneous emission functions using speed and acceleration as explanatory variables and used these functions to calculate the emission based on the output of the microscopic model PARAMICS. Ligterink et al. (2008) connected VISSIM with VERSIT+^{micro}. This emission model is a simplified VERSIT+ model, which is a regression based emission model and specifically designed to be used in combination with the output of microscopic dynamic traffic models. The main explanatory variables are vehicle category, average speed of a speed profile and the total absolute difference in instantaneous speed per km, which represents the dynamic driving behavior of a speed profile and is a measure for acceleration. This connection made with VISSIM is called ENVIVER and given the explanatory variables uses smoothed driving patterns simulated by VISSIM to calculate the emissions. PARAMICS has been integrated with the load based emission model CMEM and has been applied by Servin et al. (2006) to evaluate the impact of intelligent speed adaption (ISA) on energy use and emissions. Boriboonsomsin and Barth (2008) used this modeling framework as well, to assess the effects of freeway high-occupancy vehicle lane configuration on vehicle emissions. Within the SIMTRAP project (SIMulation of TRaffic induced Air Pollution), Angelino et al. (1999) incorporated emission modeling based on COPERT and HBEFA within the mesoscopic DTA model DYNEMO. Smit et al. (2008) applied a traffic situation emission model VERSIT+^{macro}, in conjunction with the macroscopic DTA model INDY. The VERSIT+^{macro} emission model is derived from VERSIT+ and consists of a set of composite emission factors for discrete traffic situations, which are defined by predefined ranges of quantitative traffic variables such as speed and density. Bai et al. (2007) used the mesoscopic DTA model Dynasmart-P and the average speed based emission model EMFAC to analyze trip-based versus link-based traffic data for emissions estimation.

3.6.3 Discussion

Although significant progress has been achieved in emission modeling, there are still some serious shortcomings, such as the quantity of empirical data, transferability of emission factors investigated in the laboratory or real-world traffic conditions, and model assumptions regarding the composition of vehicle fleet, driving patterns, and traffic loads on different types of roads (Corsmeier et al., 2005). Current emission models share the common base of practically all being based on laboratory measurements and a number of models (solely) use standard driving cycles in the development process, although these standard driving cycles significantly underestimate emission levels during real-world driving (Joumard et al., 2000; Smit, 2006). Next to these issues, there is limited empirical data for heavy-duty trucks (Latham et al., 2000).

Although average speed based models are frequently used, the main criticism on these approaches is that different combinations of the fundamental driving modes in a speed-time profile can give the same value for average travel speed, but significantly different emission factors (Hickman, 1999; Int Panis et al., 2006; Ahn and Rakha, 2008). The advantage of instantaneous models is that these models inherently take into account the dynamics of the driving cycle and can therefore be used to explain some of the variability in emissions associated with average speed. In addition, emissions can be calculated for any vehicle operation profile and thus new emission factors can be generated without the need for testing (Weilenman et al., 2003; Boultier et al., 2007). However, it has also been shown that for single applications (certain single driving cycles) the uncertainty is high, and instantaneous models sometimes wrongly predict trends when evaluating certain measures, which results in alterations to driving behavior. In addition, even if the response time and accuracy of the continuous measurement system is satisfactory, large variations depending on pollutant and vehicle type are observed. Also, it is possible that the process of averaging over many vehicles to obtain representative emission estimates could obscure any improvements in accuracy associated with using a detailed model. Moreover, not all instantaneous models are flexible enough to account for factors such as road grade (Hickman, 1999; Joumard, 1999; Boultier et al., 2007).

In general, the focus on emission modeling lies in the development of instantaneous power and load based emission models for microscopic applications and traffic situation models for macroscopic applications. The reason for this is that emissions during certain high-emission events, which occur during phases of high acceleration in general and during gear changes in particular, have been shown to have a large impact. The duration of such events is usually only a few seconds, but the emission level may be a multiple of the level during normal operation. This is especially true for modern petrol vehicles with closed-loop catalytic converters, which have generally a low basic emission level, but show episodes of high emissions during open-loop operation (Hickman, 1999).

The accuracy of the emission estimates are an important point of attention. More detail does not necessarily mean improvement of the estimates and does also ask for incorporating more aspects like gear changing and detailed information about car types in traffic modeling. The focus on instantaneous power and load based emission models at a microscopic level also requires accurate vehicle operations at this detailed level within a microscopic model. This accuracy is often criticized also due to the numerous modeling parameters that have to be properly calibrated and validated, which is often not performed or dealt with in an ad-hoc fashion (Hourdakis et al., 2003). One should, however, stress that these difficulties and criticisms also concern the other DTA models, although on a lower level of complexity. Even though instantaneous emission modeling in conjunction with microscopic DTA models show high potential, it's application can result in apparent accuracy. Therefore, the interconnection between DTA models and emission models should be more balanced, dependent on the accuracy of the output of the DTA model and the needed accuracy of the input of the emission model. To avoid apparent accuracy it is advisable to use traffic situation based emission models in conjunction with DTA models when the main interest of research is the influence of the dynamics in traffic conditions on the emissions.

3.7 Modeling noise

Like air quality, the assessment of noise pollution is done by estimation of the amount of sound emission in the first step and dispersion (propagation) of sound to determine the sound power levels at a receiver in the second step. Noise models presently available for noise mapping are mainly semi-empirical methods, combining the physics of sound propagation outdoors with empirical data from repeated experiments (Watts, 2005). There are different methods for quantifying the amplitude characteristics of noise. In general, the term L_{eq} (equivalent sound power level) is used, though sometimes L_{10} (the 10-percentile-level which is exceeded 10% of the time) is used. It is also common to consider the maximum level of an event, L_{max} (Robertson et al., 1998; Can et al., 2008). Traffic models are generally used to deliver input that is needed to calculate the sound emission at certain locations. That is why this section focuses at emission models, often called source models.

3.7.1 Model types

The main noise sources of traffic are rolling noise due to tire/road interaction, aerodynamic noise and propulsion noise produced by the driveline, mainly engine and exhaust, of the vehicle (El Fadel et al., 2002; Peeters, 2007). There are many factors that influence the amount of emissions. In general, at the vehicle level these are vehicle characteristics and car driver behavior (possibly influenced by the traffic situation). At the road section level these are traffic volume, road design, composition of traffic and speed. To determine sound emissions, generally functional relationships are used based on statistical analysis (Cvetkovic et al., 1998; Watts, 2005; Peeters, 2007) per vehicle type and possibly in 1/3-octave frequency bands. In most source models, rolling noise and aerodynamic noise are combined, since often the method of determination is by coast-by events. For rolling noise, this relation can be best described as a linear function of the logarithm of speed and for propulsion as a linear function of speed. The CNOSSOS model uses for example separate emission functions for propulsion noise and rolling noise (CNOSSOS, 2010). However, often rolling noise and propulsion are combined and then a linear function of the logarithm of speed is used (e.g. RMV model), because rolling noise is dominant at high speeds and those situations are most relevant concerning noise pollution. Some models distinguish different functions dependent on speed. Often, the function used is fitted for reference conditions, and for other situations deviating correction factors (γ) are used. These correction factors in most models include influence of road surface, weather and driving conditions (acceleration/deceleration). Most source models assume point sources, although some assume line sources. The models that assume point sources can use single point sources, or multiple point sources (Steele, 2001). The general formula for the sound power level (L) of a single vehicle is:

$$L = \alpha + \beta f\left(v, v^{ref}\right) + \gamma_{corrections} \qquad (3.5)$$

where f is either a logarithmic function of the vehicle speed in case of rolling and aerodynamic noise, or a linear function of vehicle speed for propulsion noise. The parameter α is the noise production of a vehicle at the reference speed at a specific distance from the road centre. If the sound power level is calculated per 1/3-octave frequency band, the parameters α, β and γ are also per 1/3-octave frequency band (Peeters, 2007).

One of the first road traffic noise models was given in the Handbook of Acoustic Noise Control (Anon, 1952). They mainly evaluate the percentile L50, defined as the sound level exceeded by the signal in 50% of the measurement period. In the years after that, the models developed towards the general form given in Equation (5). Most noise models (e.g. NORDIC, MITHRA, and NMPB) use this type of modeling to determine the sound emission at the source (Jonasson, 2003) and use different parameters for different vehicle categories (e.g. passenger cars and trucks). Distinction can be made between models in which the effects of accelerating and decelerating traffic on the sound power level is part of the corrections or part of the function. In Table 3.3 the main characteristics are presented.

Also non-European source models, like the Acoustic Society of Japan (ASJ) model, use this linear function of the logarithm of speed as the basic formula (e.g. Steele, 2001; Tansatcha et al., 2005). In relation to that, traffic conditions in terms of accelerations and decelerations that can have significant effect on sound power levels at low speeds, mainly in urban areas (when propulsion noise is dominant), are more often incorporated in source emission models (Lelong and Michelet, 1999). If taken into account as part of the corrections, these are modeled by a fixed correction or as a function of individual accelerations and decelerations of vehicles, sometimes also incorporating the used gear (Leclercq, 1999). The French 'Guide du Bruit', also used for the AR-INTERIM-CM model is the only source model found that uses different functions dependent on traffic conditions (i.e. traffic situation based). Most models assume instantaneous constant speed (uninterrupted flow) and possibly correct for acceleration, while the AR-INTERIM-CM model incorporate traffic dynamics and therefore consider average speed taking into account traffic dynamics in the emission functions (AR-INTERIM-CM, 2003).

3.7.2 Application

Jones et al. (1981) is one of the first studies found in which microsimulation is used in combination with a source emission function to assess the effects of restricted flow on noise. Two emission functions for light and heavy vehicles with explanatory variables speed and acceleration were estimated based on measurements taken from over 1,000 vehicles operating on public roads. Dynamic ROad traffic NoisE (DRONE) (Bhaskar et al., 2007) is a more recent example, which is an integration of the road traffic noise prediction model ASJ with the mesoscopic DTA model AVENUE. Riersma et al. (2004) used the average speed and volume computed by the microscopic simulation model MIXIC in combination with the Dutch RMV noise model and correction factors for road surface to determine an optimal speed limit on Dutch motorways. Within the EU project ROTRANOMO a simulation tool has been developed consisting of the microscopic dynamic model VISSIM and a vehicle noise model that uses the road surface, vehicle acceleration, normalized engine speed and load (using a drivetrain model as pre-processor to estimate engines speed and load) to calculate rolling noise and propulsion noise (Volkmar, 2005). De Coensel et al. (2005) developed a model for noise prediction using the microscopic DTA model Quadstone PARAMICS and the NORD2000 noise emission database, which means emissions are a function of vehicle type and speed (in the form of tables). This means no subdivision in propulsion noise and rolling noise is made and also no corrections for acceleration or deceleration or road surface are taken into account. De Coensel (2006) carried out a case study of a large set of intersection scenarios using the same Quadstone PARAMICS plugin, combined with the Harmonoise model, to estimate spatial correction factors dependent on vehicle operations. Leclercq (1999) developed a model constructed from a combination of sound power level values of vehicles, measured on test tracks in urban driving conditions, and of a macroscopic dynamic representation of traffic flow (i.e. DNL model). In this model, the speed and acceleration of vehicles were derived from the DNL model. The emission modeling was based on speed, acceleration, gear ratio (estimated) and a noise emission monogram using this input. Can et al. (2008) tested different traffic and noise source representations for sound power level estimation. The different traffic representations were essentially a macroscopic DNL model and two types of microscopic simulation models with different car-following rules, only taking passenger cars into account. They concluded that a macroscopic DNL model is sufficient for noise assessments in urban traffic conditions, but can be improved by using microscopic simulation models. The emission laws they used consist of rolling noise dependent on speed and propulsion noise dependent on speed and cruising mode (acceleration, cruising, or deceleration). The cruising mode was determined by the differences in vehicle speed between two time steps. Can et al. (2009) made a comparison between noise assessments using static (basic and a refined approach) and dynamic traffic models. The noise model consisted of different emission functions for accelerations, cruising and decelerations (mainly different for the low speed areas in which propulsion noise dominates) for passenger cars and buses, which are used within the French traffic noise prediction model. They found that the basic application of a STA is not refined enough to guarantee precise noise estimates. The refined static calculation based on mean kinematic patterns could be sufficient to estimate equivalent noise levels for most cases. However, incorporating more dynamics improves noise estimations. Chevallier et al. (2009b) used the same emission functions to develop a new microscopic traffic simulation tool (in their research only for light duty vehicles) for roundabouts that can support noise emission assessment. Chevallier et al. (2009a) compared a static noise model, an analytic noise model, and a microscopic simulation model to obtain noise levels at signalized intersections and roundabouts. For all models the same source emission model was used based on the FHWA noise emission database, in which the sound power level depends on vehicle speed and throttle conditions (cruising or full) and consists of one single function for rolling noise and propulsion noise. They found that accounting for traffic dynamics improves predictions of noise variations. King and Rice (2009) developed a practical framework for strategic noise mapping and used different emission functions based on the EU project AR-INTERIM-CM. The function used depends on speed in the case of one of four flow types (fluid continuous flow, pulsed continuous flow, pulsed accelerated flow or pulsed decelerated flow) and one of three gradient types (up, down, or flat) and a correction for road surface. Within this model, the emission levels are calculated and then a standard frequency distribution is used to transform the overall A-weighted levels into octave band levels.

3.7.3 Discussion

It can be stated that relatively little research has been conducted in assessing noise in conjunction with DTA models. Most efforts done to assess noise use microscopic models. However, there are some efforts to assess the effects using macroscopic or mesoscopic dynamic models and the methods available can be used. In Leclercq (1999) and De Coensel et al. (2005) is concluded that there are several benefits in considering dynamics of traffic in order to improve road noise emissions estimates, because of identifying local peaks and variations. Within the literature, there is hardly any discussion found about the suitability of noise models, probably also because many models in this area are similar. However, within the EU project IMAGINE it is concluded that current traffic models, in their various forms, can be used to produce the data needed for noise modeling, but their link is not unambiguous. There are several weak points concerning intrinsic model characteristics and the accuracy (TNO, 2005). Also for noise applies that, although noise modeling in conjunction with microscopic DTA models show high potential, it’s application can result in apparent accuracy. Incorporating aspects like gear changing, and a higher level of accuracy in modeling vehicle operations for microscopic applications is necessary. For macroscopic applications the various methods can be used.

Table 3.2 Examples of the difference between free and interrupted flow (Jonasson, 2003)

	***L*Aeq [dB]**			
Vehicle	**Free-flow** 20m/s (25 s)	**Interrupted** (54 s)	**Interrupted** normalized to 25 s	**Free-flow** 9.2 m/s (54 s)
FORD MONDEO	73.9	70.2	**73.5**	62.8
VOLVO S40	75.5	70.1	**73.4**	63.8
VOLVO S40 Diesel	75.2	70.4	**73.7**	64.8
FORD Ka	73.1	68.3	**71.6**	62.6
TOYOTA PREVIA	74.7	69.5	**72.8**	64.0
TOYOTA Hi-Lux	74.5	70.2	**73.5**	64.8
MITSUBISHI PAJERO	75.5	71.1	**74.4**	66.3
MC – BMW 650	75.6	71.8	**75.1**	64.6

Point of attention is the correction or incorporation of the effects of acceleration and deceleration. In literature there is some debate on the necessity of taking these effects into account when using a macroscopic DTA or STA model. Often correction factors are used, because the uncertainty in estimation of individual accelerations and decelerations is higher than the effect on noise (CNOSSOS, 2010). In Jonasson (2003) it is stated that based on simulation experiments, it is probably not necessary to make noise corrections for interrupted flow, at least not when traffic is moderate. However, given the results (presented in Table 3.2) this conclusion is probably based on the normalized values and rather remarkable, because the difference in sound power level between uninterrupted flow driving 9.2 m/s and interrupted flow driving the same average speed is roughly 6 dB(A).

3.8 Concluding remarks

In this chapter the externalities congestion, air quality, climate, noise and traffic accidents have been selected, because these are a result of the actual use of a traffic system. The effect assessment of external effects can be improved by using temporal information about flow, speed and density, which is output of DTA models. DTM measures influences the actual use of traffic systems as well as traffic dynamics and can therefore be used to optimize externalities. Given the available externality models, there is still a gap in knowledge to assess traffic safety based on the output of DTA models. For now only accident risk based models or possibly APMs at the aggregate level (using AADT) can be used in conjunction with macroscopic DTA models and possibly SPIs for microscopic DTA models. However, there are little APMs available that include traffic dynamics as an explanatory variable and almost none has been estimated for urban roads due to a lack of sufficient data for these types of roads. For modeling emissions, instantaneous power, modal models and load based emission models for microscopic applications and traffic situation models for macroscopic applications are probably most suitable. Although relatively little research is done in assessing noise in conjunction with DTA models, the methods available to determine the source emissions in conjunction with dynamic models are suitable. Point of attention however, is the incorporation of the effect of accelerations and deceleration, especially at urban roads. Most efforts in assessing external effects with DTA models use microscopic models. This does not necessarily mean an improvement of the estimates and also asks for incorporating more aspects like gear changing (relevant for emissions and noise) in traffic modeling, which is not common output of these models. The accuracy of these traffic models at the detailed level needed for the assessment methods developed at microscopic level can result in apparent accuracy. Therefore, the interconnection between DTA models and external effect models should be balanced depending on the accuracy of the output of the DTA model and the needed accuracy of the input of these models. Based on these findings appropriate methods are chosen in Chapter 4 to assess the effects of DTM strategies.

Table 3.3 Overview model types for externality modeling

Model type	Function type	Input level	Road Characteristics	Vehicle characteristics	Driving characteristics	Traffic characteristics	Example
				Traffic safety			
ARBM	Continuous	Road section	Road type, intersection type	-		Flow	
APM	Continuous	Road section	Road type, intersection type	-		Flow, (speed, density)	
SPI	Discrete	Continuous	-	(Vehicle class)	Space-time behavior individual vehicles/interaction vehicles	(shockwaves, delay)	TTC, NOC, PCE
				Emissions			
Aggregated emission function	Discrete	Trip or road section	Road type	Vehicle class		Flow	NAEI, CAR, EMFAC, VFEM
Traffic situation	Discrete	Road section	Road type	Vehicle class		Flow, Level of service	HBEFA, ARTEMIS
Average speed	Continuous	Trip	-	Vehicle class		Flow, (Adjusted) Average speed	COPERT, MOBILE, TEE, QUARTET
Regression	Continuous	Trip	Road design	Vehicle type	Driving cycle	-	VERSIT+
Driving mode/modal	Discrete	Road section	-	Vehicle class	Distribution of driving modes	-	UROPOL, MEASURE, MOVES
Instantaneous/speed based	Discrete/ continuous	Continuous	-	Vehicle class	Driving-cycle (speed/acceleration)	-	DGV, MODEM
Instantaneous/power based	Continuous	Continuous	-	Vehicle type, engine load	Driving-cycle, used gear	-	CMEM, EMIT, PHEM, VeTESS
				Noise			
Instantaneous/speed based	Continuous	Road section	Surface type, wetness, gradients.	Vehicle class	Acceleration/ deceleration, (used gear)	Flow, speed	Harmonoise, CNOSSOS, NORDIC, MITHRA, RMVII, NMPB, ASJ
Traffic situation /speed based	Continuous	Road section	Surface type, gradients	Vehicle class	Traffic situation	Flow, average speed	AR-INTERIM-CM

Chapter 4

Modeling framework

Het goede doel is niet je eigen doel
The correct goal is not your own goal
Johan Cruijff

In chapter 1 the research objectives and challenges were presented. The challenge regarding modeling of externalities using DTA models, based on the extensive literature review presented in Chapter 3, is addressed in this chapter. Before that the optimization problem is mathematically formulated and the general framework is presented. The multi-objective optimization problem in which the decision variables are DTM measures on a strategic level and the objectives are maximizing accessibility and minimizing externalities, is a bi-level optimization problem. In this bi-level optimization problem the system objectives are optimized by road management authorities at the upper level and at the lower level road user optimize their own objectives. Both levels are interdependent, because road management authorities determine the settings of the DTM measures based on the behavior of road users, and road user adapt their behavior based on the traffic conditions that are influenced by the DTM measures.

This chapter presents the general framework. After describing the optimization problem mathematically, the modeling of the externalities is presented. To be able to optimize the objectives, the used objective functions, which all represent a network measure, are formulated. After that, the modeling of the DTM measures is presented as well as the used Streamline DTA model and its characteristics. This chapter also introduces the cases used in this research and are referred to in the next chapters.

4.1 Optimization problem

The optimization of externalities using DTM measures is formulated in this research as a MO NDP with discrete decision variables. In this bi-level optimization problem the lower level describes the behavior of road users that optimize their own objectives (e.g. travel time and travel costs). At the upper level the objectives are optimized by the stakeholders who can deploy the DTM measures in a certain way (i.e. road management authorities). In this research it is assumed that the stakeholders at the upper level cooperate and are trying to minimize the externalities (accessibility inclusive) using the available DTM measures. The minimizations of externalities are therefore the joint objectives of these road authorities, which can be the outcome of a STM process. The lower level is operationalized by solving the dynamic UE problem assuming fixed demand using a DTA model. Because the NDP is a NP-hard optimization problem (Gao et al., 2005; Chiou, 2005a), heuristics are needed to solve the upper level.

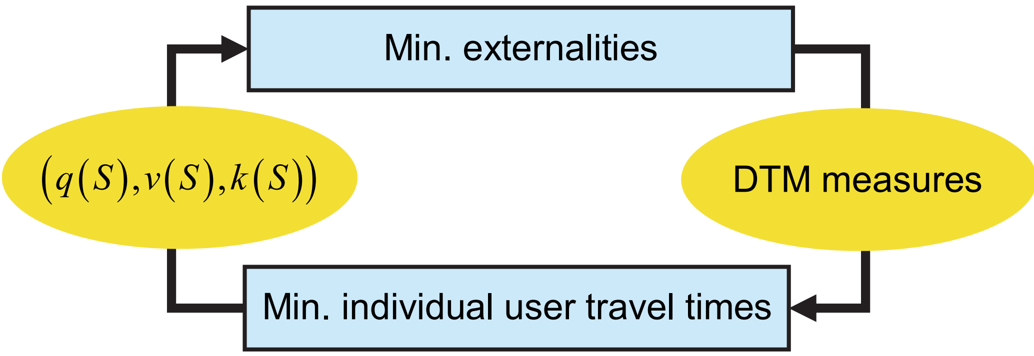

Figure 4.1 Bi-level optimization problem

The bi-level MO NDP problem is formulated as an equivalent MO MPEC (mathematical problem with equilibrium constraints):

$$\min_{S\in F}\begin{pmatrix} z_1(S) \\ z_2(S) \\ \vdots \\ z_I(S) \end{pmatrix}, \quad \text{subject to} \quad (q(S),v(S),k(S)) \in \Gamma^{DTA}\left(G\left(N,A\left(C(S)\right)\right),D\right), \quad \text{and}$$

$$F=\left\{S \mid s_b^t \in \{1,\ldots,M_b\}, \forall b,t\right\} \tag{4.1}$$

in which S is a set of applications of strategic DTM measures to be selected from a set of feasible applications F, and $z_i(S)$, $i=1,\ldots,I$, are the objective functions, which are a function of the link flows $q(S)$, the link speeds $v(S)$, and the link densities, $k(S)$, expressed as $z_i(S)=f_i\left(q(S),v(S),k(S)\right)$. These objectives in this research concern efficiency (as a measure for accessibility), climate, air quality, traffic safety and noise. Furthermore, the link flows, speeds, and densities are assumed to follow from solving a dynamic UE problem, indicated by Γ^{DTA}, for which the supply of infrastructure is given by G with nodes N and links A (with corresponding characteristics C), and the travel demand D. Each link a has specific characteristics C_a The link characteristics without any DTM measures, which is denoted by C_{a0}, include the capacity, outflow capacity, the number of lanes, the free-flow speed, the speed at capacity, and the jam density, and are captured in a fundamental diagram (q_c,q_o,l,v_f,v_c,k_j). A time period is considered consisting out of T time intervals related to the DTM measures. Therefore $t\in\{1,\ldots,T\}$ in which t is an interval of $\left[(t-1)\Delta t,t\Delta t\right]$. Next to the link characteristics C, the link flows $q(S)$, the link speeds $v(S)$, and the link densities, $k(S)$, also travel demand D is time dependent. However, the time intervals distinguished are different for supply of infrastructure, travel demand and the temporal information on resulting link flows, speeds and densities. For the sake of clarity this is not incorporated in the formulation.

The DTM measures considered and defined in S are the measures that influence the supply of infrastructure (e.g. traffic signals, ramp metering, rush hour lanes or dynamic speed limits). By solving the dynamic UE problem, the route choice effects of changes in the supply of infrastructure are taken into account. However, this also means that DTM measures that influence route choice behavior directly (e.g. providing route information) are not considered. The DTM measures are modeled as measures that influence the characteristics C of the links where the measures are implemented, i.e. the supply of infrastructure. This means for example that when a Variable Message Sign (VMS) is used to change the speed limit, the free speed and possibly capacity of the links connected with this measure are changed. The characteristics C of links can therefore vary over time depending on the settings of the DTM measures, S. The impact of a measure depends on the actual settings, e.g. the green time for a certain direction on a signalized intersection. Activation times and settings of the DTM measures are discretized, so the upper level then becomes a discrete optimization problem where for each time period a certain DTM measure with a certain setting is implemented or not. The set of feasible solutions, F, is assumed to be a discrete set of possible applications of strategic DTM measures. Assuming that there are B different DTM measures available in the network, the deployment of the DTM measures in time step t is defined by $S^t = \left(s_1^t,...,s_B^t\right)$, where each s_b^t, $b = 1,\ldots,B$, can have M_b different settings, which are simply numbered from 1 to M_b. The set of feasible solutions can therefore be written as $F = \left\{S \mid s_b^t \in \{1,\ldots,M_b\}, \forall t = 1,\ldots,T\right\}$, such that there are $\left(\prod_b M_b\right)^T$ possible solutions. The deployment of the DTM measures for all time periods is defined by $S = \left(S^1,...,S^T\right)$ and forms a possible solution for the optimization problem. $C_a\left(s_b^t\right)$ is defined as the characteristics of link a as a result of setting s of measure b during time interval t. The characteristics of link a as a result of the combined deployment of the available DTM measures during time interval t is defined by $C_a\left(S^t\right)$. The solution S_i^* represents the optimal solution for objective i and $X^* = \left\{S_1^*,..,S_j^*\right\}$ the Pareto optimal set, which is the outcome of the MO NDP. The Pareto optimal set consists of all solutions for which the corresponding objectives cannot be improved for any objective without degradation of another.

As shown in this formulation, the optimization problem incorporates dynamic travel demand and supply of infrastructure that changes over time as a result of DTM settings. The DTM measures are modeled as time dependent measures and this travel demand and supply of infrastructure is input for the DTA model. This model provides temporal information on traffic flows, speeds and densities per link. The decision variable S within the optimization of objective functions z_i only influences supply of infrastructure. It is assumed that demand is not influenced by the decision variable (i.e. fixed demand is assumed).

4.2 Modeling externalities

4.2.1 Congestion

DTA models are primarily designed to evaluate traffic systems in terms of the resulting traffic situation as a consequence of the way road users will react on measures taken. Therefore indicators related to objectives concerning accessibility or congestion can be directly derived from the outcome (i.e. temporal information on traffic flows, densities and speeds) of these

DTA models. For all other objectives related to the externalities, externality models have to be connected to the DTA model. As explained in Chapter 3, additional models are needed to assess the effects on traffic safety, climate, air quality and noise. This paragraph explains the way these externalities are modeled in the optimization framework. The choices made are based on the results of the presented review in Chapter 3.

4.2.2 Traffic safety

Traffic safety is represented by the measure of the number of accidents, injury accidents, fatalities or seriously injured. Because there are no APMs available that cover all road types in a network, a risk based traffic safety model is used in which the relation between exposure (number of vehicle kilometers, $q_a \ell_a$) and risk per road type (ratio of number of injury accidents per vehicle kilometer, R_d) is used. The number of injury accidents is calculated for links in which the injury accidents on intersections are incorporated. This means that the influence of density of intersections on a road, intersection types, crossing flows and therefore the level of potential conflicts is averaged per road type. The number of injury accidents on link *a*, is calculated by:

$$\text{number of injury accidents}_a = \sum_t \sum_m q_{am}(t) R_d \ell_a \tag{4.2}$$

Important point of attention of this calculation method is that it can only deal with the effect of the dynamics of route choice of road users (i.e. use of different road types) and not with the traffic dynamics on a certain road (speed and speed differences). As explained in chapter 3, this information, which could be part of APM, is lacking to assess all existing link types of a network. In the literature, there is typically no distinction made in accident risks between vehicle types. Table 4.1 presents the used injury accident risk figures from the Netherlands (Jansen, 2005). The number of injury accidents is used as the indicator for traffic safety.

Table 4.1 Overview of used risk figures

Road type *d* (Sustainable safe definitions)	**Risk (R_d) injury accidents/million vehicle kilometers**
Through-road	0.07
Non-urban distributor roads	0.22
Urban distributor roads	1.10
Non-urban access roads	0.43
Urban access roads	0.57

4.2.3 Climate and air quality

The effect of traffic on climate is represented by the measure of the amount of CO_2 emitted by traffic. The effect of traffic on air quality is represented by the amount of NO_x or the amount of PM_{10} emitted by traffic. Besides NO_x and PM_{10} there are also other pollutants relevant for air quality. However, these two pollutants are the most critical in the Netherlands in relation to the EU limit values. Although, it is straightforward to calculate these emissions using the output of the DTA model, the real measure of air quality is the concentration of these substances at certain locations. These concentrations depend on weather conditions, type of road surface and the location of screens and buildings. Information on these aspects is not standard available in transport models, but necessary to calculate the dispersion. As will be explained in paragraph 4.3, this dispersion modeling is not addressed in this framework.

In Chapter 3 it was concluded that traffic situation based emission models are appropriate emission models to calculate emissions based on a DTA model. The calculation of the emissions of CO_2, NO_x and PM_{10} is therefore based on a traffic situation based emission model ARTEMIS (INFRAS, 2007) in this research. This model distinguishes four different traffic states for which different emission factors are available (free flow, heavy traffic, quasi-saturated and stop & go, see Figure 4.2). The ARTEMIS emission model (Assessment and Reliability of Transport Emission Models and Inventory Systems) has been developed within the identically named European project. The model basically contains an emission factor database and provides procedures to calculate emissions. Within this model four different traffic states are distinguished for which emission factors are available per link type (i.e. 5 rural types and 7 urban types) and vehicle type (i.e. fuel type, legislation class). Based on estimates of the Dutch fleet data of 2008 (Janssen et al., 2006) emission factors $E_{md}^{(\cdot)}$ are determined per link type d and vehicle class m and PM_{10} emissions due to abrasion are added. The emission on link a, is calculated by:

$$\text{emission of substance}_a = \sum_t \sum_m q_{am}(t) E_{md}^{(\cdot)}\left(v_{am}(t)\right) \ell_a \tag{4.3}$$

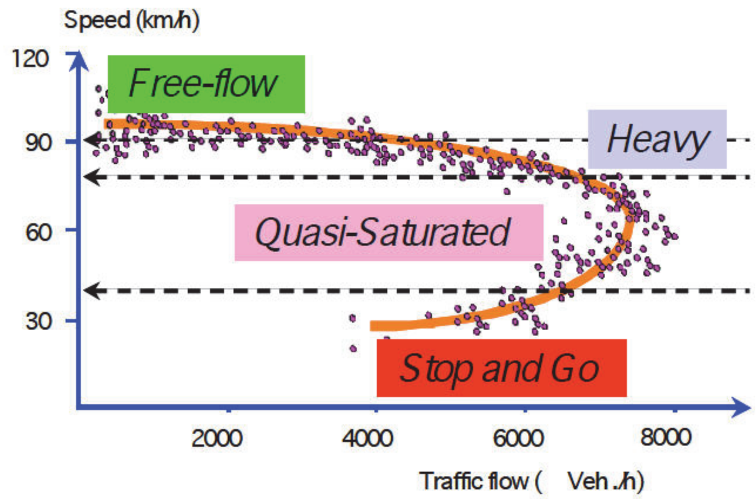

Figure 4.2 Distinguished traffic states for modeling emissions (source INFRAS, 2007)

For every time interval (default 5 minutes) the DTA model calculates speeds, flows and densities. Based on this information the traffic state is determined (see Figure 4.3) to calculate the emissions of substances.

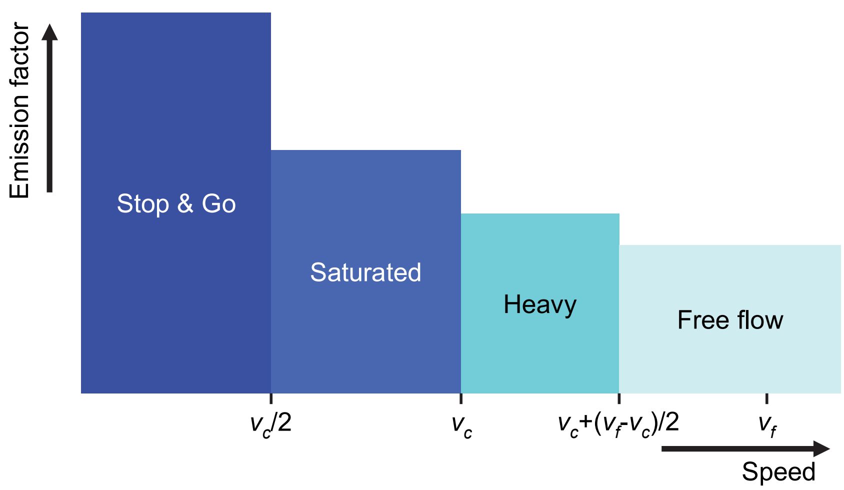

Figure 4.3 Connection emission factor and speed

4.2.4 Noise

The generation of noise pollution by traffic is represented by the sound power level at the source (L_{am}). Like air quality, this measure is calculated using the output of the DTA model. However, the real measure of noise pollution is the sound power level at particular locations. To determine such sound power levels, information is needed concerning type of road surface, the alignment of the road and the location of screens and buildings to calculate the propagation of sound. Information on these aspects is not standard available in transport models, but necessary to calculate the propagation. As will be explained in paragraph 4.3, this propagation modeling is not addressed in this framework. In Chapter 3 it was concluded that all noise emission models in general use functional relationships per vehicle type in which speed is the explanatory variable. Traffic dynamics are therefore taken into consideration. Two calculation methods are used in this research to calculate the sound emissions.

The first method is the regression function per vehicle category that is estimated within the RMV method (RMV, 2006), which calculates the sound power level on link a for vehicle category m:

$$L_{am}\left(v_{am}(t)\right) = \alpha_m + \beta_m \log\left(\frac{v_{am}(t)}{v_m^{\text{ref}}}\right) + 10\log\left(\frac{q_{am}(t)}{v_{am}(t)}\right) \tag{4.4}$$

To calculate the total sound power level, the emissions of the different vehicle categories are energetically added and to calculate the average sound power level over time the emissions are energetically averaged. The parameter settings used are 80 and 70 km/h for the reference speeds v_m^{ref} for passenger cars and trucks, and $\alpha_m = 69.4$ (76.0) and $\beta_m = 27.6$ (17.9) for passenger cars (trucks). An important point of attention of this method is that it is a combination of rolling and propulsion noise and therefore focused on the rolling noise. Rolling noise is dominant at higher speeds, typically higher than 40 km/h for passenger cars, depending on road surface. Propulsion noise is mainly of interest at lower speeds, especially when a vehicle is accelerating. No correction factors are used for acceleration and deceleration or for road surface. The latter is not incorporated, while information concerning the road surface is generally not available within DTA models, but can be incorporated using correction factors of the RMV model.

The second method is used to incorporate the effects of acceleration and deceleration. This method is based on the AR-INTERIM-CM model (Adaptation and Revision of INTERIM Computation Methods for the purpose of strategic noise mapping (AR-INTERIM-CM, 2003). The AR-INTERIM-CM model is based on the French 'Guide du Bruit' (Cetur, 1980) and developed in the identically named European project. This method distinguishes four different emission functions that depend on flow types (i.e. fluid continuous flow, continuous pulsed flow, pulsed accelerated flow or pulsed decelerated flow) and three gradient types (i.e. (up, down, or flat). The main difference between the RMV method and this method, is that the RMV method uses a function depending on instantaneous constant speed for uninterrupted flow and the AR-INTERIM-CM model depending on average speed. The latter one incorporates the influence of the level of acceleration and deceleration, while the RMV model does not. In Figure 4.4 the different emission functions are shown for light vehicles and flat surface, compared with the RMV method. Note that the noise emissions of the AR-INTERIM-CM model are corrected for the difference in reference distance from the source between the two methods.

The sound power level on link *a* for vehicle category *m,* is calculated by:

$$L_{am}\left(v_{am}(t)\right)=\alpha_m\left(v_{am}(t)\right)+\beta_m\left(v_{am}(t)\right)\log\left(\frac{v_{am}(t)}{v_m^{\text{ref}}}\right)+10\log\left(q_{am}(t)\right) \tag{4.5}$$

To calculate the total sound power level the emissions of the different vehicle categories are energetically added and to calculate the average sound power level over time the emissions are energetically averaged. The parameter settings used are 20 for the reference speeds v_m^{ref} for passenger cars and trucks, and the parameters α_m and β_m depend on flow type, vehicle category, gradient and speed interval and are presented in AR-INTERIM-CM (2003). The flow types describe the traffic characteristics on a link:

- Continuous fluid flow: this is a fluid flow (stable temporal and spatial vehicle rate), where the vehicles have a significantly steady speed (e.g. non-congested motorways).
- Continuous pulsed flow: this is a pulsed flow or transient speed (acceleration or deceleration), neither spatially nor temporally stable, but one for which it is nonetheless possible to define a mean vehicle flow speed (e.g. congested motorways).
- Accelerated pulsed flow: this is a pulsed, therefore turbulent flow, but one where a large percentage of vehicles are in acceleration (e.g. road downstream an intersection).
- Decelerated pulsed flow: this is a pulsed, therefore turbulent flow, but one where a large percentage of vehicles are in deceleration (e.g. motorway exit).

For the calculation of the sound power level based on this AR-INTERIM-CM model, only the first two types are taken into consideration, because of the characteristics of the DTA model used. Based on the speed calculated on a link for every output time interval (default 5 minutes), the flow type (i.e. continuous fluid if calculated speed is higher than v_c or continuous pulsed if calculated speed is lower than v_c) is determined for this time interval, which is connected with a certain emission function.

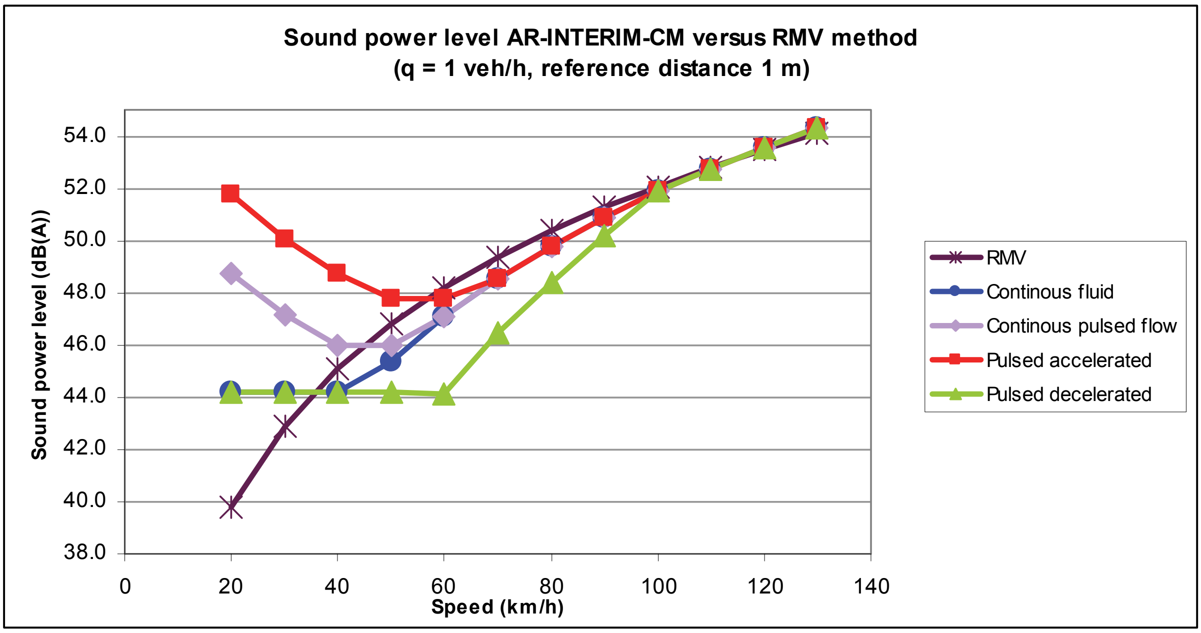

Figure 4.4 Comparison RMV and AR-INTERIM-CM model (light vehicle)

4.3 Objective functions

In the optimization problem it is assumed that the stakeholders (i.e. road management authorities) at the upper level cooperate in deploying the DTM measures. Their multiple objectives to optimize are related to accessibility and the external effects of traffic. However,

Table 4.2 Overview of measures and objective functions used

Objective	**Measure**	**Remark**
Efficiency	Total travel time (h)	Because fixed demand is assumed, minimizing total travel time is equal to minimizing vehicle loss hours.
$z_1 = \sum_a \sum_t \sum_m \frac{q_{am}(t)\ell_a}{v_{am}(t)}$		(4.6)
Traffic safety	Total number of injury accidents	Calculation based on using the relation between exposure and risk per road type.
$z_2 = \sum_a \sum_t \sum_m \sum_d q_{am}(t)\delta_{ad}^R R_{md}\ell_a$		(4.7)
Climate	Total amount of CO_2 emissions (grams)	Calculation based on traffic situation based emission model ARTEMIS.
$z_3 = \sum_a \sum_t \sum_m \sum_d q_{am}(t)\delta_{ad}^E E_{md}^{\mathrm{CO2}}\left(v_{am}(t)\right)\ell_a$		(4.8)
Air quality	Weighted total amount of NO_x emissions (grams) Weighted total amount of PM_{10} emissions (grams)	Calculation based on a traffic situation based emission model ARTEMIS. Two substances NO_x and PM_{10} are assessed.
$z_4 = \sum_a \sum_t \sum_m \sum_d w_a q_{am}(t)\delta_{ad}^E E_{md}^{NO_x}\left(v_{am}(t)\right)\ell_a$		(4.9)
Noise	Weighted average Sound Power Level at the source (dB(A))	Calculation based on the RMV or AR-INTERIM-CM model.
$z_5 = 10\log\left(\frac{\sum_a \sum_w \delta_{aw}\ell_a 10^{\frac{\bar{L}_w - \eta_w}{10}}}{\sum_a \sum_w \delta_{aw}\ell_a}\right)$, with $\bar{L}_w = 10\log\left(\frac{\sum_a \sum_t \delta_{aw}\ell_a \Delta t \sum_m 10^{\frac{L_m(v_{am}(t))}{10}}}{T\sum_a \delta_{aw}\ell_a}\right)$		(4.10)

with

- z_1 : Objective function efficiency (= total travel time) (h)
- z_2 : Objective function traffic safety (= total number of injury accidents)
- z_3 : Objective function climate (= total amount of CO_2 emissions) (grams)
- z_4 : Objective function air quality (= weighted total amount of emissions of substance *s*) (grams)
- z_5 : Objective function noise (= weighted average sound power level at source) (dB(A))
- $q_{am}(t)$: Vehicle type *m* inflow to link *a* at time *t* (veh)
- $v_{am}(t)$: Average speed of vehicle type *m* on link *a* at time *t* (km/h)
- R_{md} : Injury accident risk of vehicle type *m* for road type *d* (injury accidents/(veh*km))
- $E_{md}^{\mathrm{CO2}}(\cdot)$: CO_2 emission factor of vehicle type *m*, depending on average speed (grams/(veh*km))
- $E_{md}^{NO_x}(\cdot)$: Emission factor of NO_x of vehicle type *m* on road type *d*, depending on average speed (grams/(veh*km))
- $L_m(\cdot)$: Average sound power level for vehicle type *m*, depending on the average speed (dB(A))
- $\bar{L}_w$: Weighted average sound power level on network part with urbanization level *w* (dB(A))
- ℓ_a : Length of link *a* (km)
- δ_{ad}^R : Safety road type indicator, equals 1 if link *a* is of road type *d*, and 0 otherwise
- δ_{ad}^E : Emission road type indicator, equals 1 if link *a* is of road type *d*, and 0 otherwise
- δ_{aw} : Urbanization level indicator, equals 1 if link *a* has urbanization level *w*, and 0 otherwise
- η_w : Correction factor for urbanization level *w* (dB(A)))
- w_a : Level of urbanization around link *a*
- α_m, β_m : Parameters dependent on vehicle type for noise calculations
- v_m^{ref} : Reference speed dependent on vehicle type (km/h)
- Δt : Time interval output data DTA model
- T : Total assessed time period

in most countries there are several road management authorities that control their own DTM measures and which can have different and possible conflicting objectives. To reduce complexity objective functions expressing the network performance are formulated, resulting in one function per objective and therefore also jointly formulated objective functions. However, the framework presented can also be used if more objective functions are formulated also for parts of the network (e.g. per road management authority). Assuming this cooperation means that the self-interest of the various road management authorities is not considered. The jointly formulated objectives can be the outcome of STM processes (AVV, 2003). The formulated objectives and possible constraints can be different for specific cases. In this research objective functions are formulated that can be applied in general and presented in Table 4.2.

The objectives accessibility and congestion are related and named efficiency in this optimization problem. There are many definitions for accessibility. However, assuming that accessibility refers to the ability and ease to reach destinations (to transport goods, to reach services or to do activities), means minimizing travel times in the case of fixed demand. The externality congestion concerns the additional travel time inflicted by a road user to other road users, which means minimizing delay. Increasing congestion problems leads to deteriorating accessibility. Because fixed demand is assumed, minimizing travel times is equivalent to minimizing delay.

The objective traffic safety concerns the actual number of accidents and their level of severity. The objective function focuses on minimizing injury accidents. The injury accidents consist of the accidents with a fatal outcome or people getting injured.

Traffic is an important and relatively increasing source of the anthropogenic CO_2-emissions, which is a greenhouse gas. Minimizing the total emissions of CO_2, reduces the adverse effects on our climate, which is the objective function.

Traffic is also one of the major contributors of emissions of substances deteriorating the air quality and emissions of noise. However, in contrast to CO_2-emissions, the location where these substances and noise are emitted is of interest. The best indicators for air quality and noise are therefore the concentration of these substances at certain locations respectively the sound power level at particular locations. The limit values for these externalities are also formulated on this level. If obeying these limit values is the objective, these externalities should be considered as a constraint. However, it can be argued that these externalities should be considered as an objective rather than a constraint, because the objective should be to improve for instance air quality instead of being able to stay below a certain threshold (i.e. why is a concentration of 39.9 $\mu g/m^3$ PM_{10}, which is below the limit value, not a problem and 40.1 $\mu g/m^3$ PM_{10} is). Next, for air quality the background concentration (traffic in general included) mainly influences the available space to manage a network. This also means that reducing emissions on other locations can help reducing emissions on a particular location, because the background concentration reduces. To calculate the concentrations of substances, dispersion models are needed and to calculate the sound power levels propagation models are needed. As indicated in Chapter 2 dynamic MO NDP is a computational expensive optimization problem even without applying dispersion and propagation models and these models need additional information that is not standard available in DTA models. The emissions are directly related tot the concentrations and sound power levels. The total emissions of NO_x or PM_{10} and average sound power level at the source are therefore already good indicators to calculate the network performance on these objectives. In addition, it is questionable how best to aggregate concentrations or sound power levels at certain locations to judge the network performance in terms of air quality and noise. Though, it is a fact that these externalities are related to human health and therefore, it is of importance what concentrations or sound power levels are calculated at particular locations. High concentrations in residential areas are more harmful than high concentrations in rural areas. That is why weights are used per road section dependent on level of urbanization. Within this research three levels of urbanization are distinguished, highly urbanized, urbanized and rural. The weights used for emissions of NO_x and PM_{10} (w_a, respectively 3, 2 and 1) are based on the dilution factor that is used in the CAR emission model (Infomil, 2007). This factor depends on the distance and to what extent buildings are present near the road (e.g. street canyons). Also, for noise pollution it can be stated that high sound power levels in residential areas are more harmful or irritating than high sound power levels in rural areas. That is why correction factors are used dependent on the urbanization level. The same levels of urbanization, w, are used as for air quality, highly urbanized, urbanized and rural. The correction factors (η_w, respectively -7, -10, -13) are based on the distance correction factor used in the Dutch RMV standard calculation method (RMV, 2006). The objective functions used, which all should be minimized, are listed in Table 4.2.

4.4 Modeling of measures

4.4.1 Characteristics

To reduce the number of decision variables, the DTM measures defined in *S* are modeled as measures that influence the characteristics *C* of the links where the measures are implemented as was stated before. The characteristics *C* of links can vary over time, dependent on the settings of the DTM measures, *S*. This means that the DTM measures are modeled as time dependent measures and not as traffic responsive. The impact of a measure depends on the actual settings, e.g. the green time for a certain direction on a signalized intersection. This also means that the measures that are considered have to influence the supply of infrastructure explicitly and other DTM measures that focus on changing driver's behavior on a voluntary basis (for instance by providing route information) are not taken into account. The measures considered are grouped in three major classes: traffic lights, variable lane configuration and variable speed limits, which represent all current possible applications. With these measures it is e.g. possible to set up applications as ramp metering, tidal flow, rush hour lanes and buffering. Time and settings of the DTM measures are discretized, so the upper level then becomes a discrete optimization problem where for each time period a certain DTM measure with a certain setting is implemented or not. The set of feasible solutions, *F*, is assumed to be a discrete set of predefined possible applications of strategic DTM measures. Assuming that there are *B* different DTM measures available in the network, the deployment of the DTM measures in time step *t* is defined by $S^t = \left(s_1^t, ..., s_B^t\right)$, where each s_b^t, $b = 1, \ldots, B$, can have M_b different feasible settings, which is simply numbered from 1 to M_b. The characteristics of all links in the network is a function of these settings, $A\left(C\left(S^t\right)\right)$. This representation of the solution also prevents considering infeasible solutions and reduces the design variables by using one decision variable per DTM measure.

Table 4.3 Link characteristics influenced by measures

Measure classes	**Link characteristics**					
	q_o	l	q_c	v_f	v_c	k_j
Traffic signal	x					
Variable lane configuration		x	x	(x)	(x)	
Variable speed limit			(x)	x	x	

The different M_b settings and ways these are modeled by changing link characteristics, have to comply with possible actual settings of these measures and possible local effects of these measures on the link characteristics. Changing for example the number of lanes results in a change of link capacity, but also changing the speed limit can result in a change of link capacity. The settings of the link characteristics for the different measures are case specific, which means no generic values are provided in this research. However, changing speed limits or number of lanes is closely related to the model parameters used, which is not the case for traffic signals. For this measure the outflow capacity of the link is used to model the influence of the deployment of a certain signal plan. Modeling of traffic signals will be separately discussed. Table 4.3 gives an overview of measures and link characteristics used to model them.

4.4.2 Modeling of traffic signals

By modeling DTM measures using the link characteristics means that traffic signals are not precisely modeled as in reality. This choice is made to minimize decision variables and therefore reducing the complexity, but also because this is the easiest and fastest way to change the supply of infrastructure within the DTA model externally. In this framework the average outflow capacity per incoming link q_{ao} is directly used, instead of being the result of the effective green time g_a part of the total cycle time CT ($q_{ao} = q'_{ac} \, {}^{g_a}\!/_{CT}$, in which q'_{ac} being the corrected capacity of link a as a result of lane configuration and a permitted turning movement allowing conflicts). The effective green time g_a equals the time actually available and depends on the actual green time, yellow time and applicable lost times. To simplify the optimization problem and reducing decision variables, it is assumed that all directions from one incoming link receive green in the same phase, which means the total outflow capacity of an incoming link is controlled.

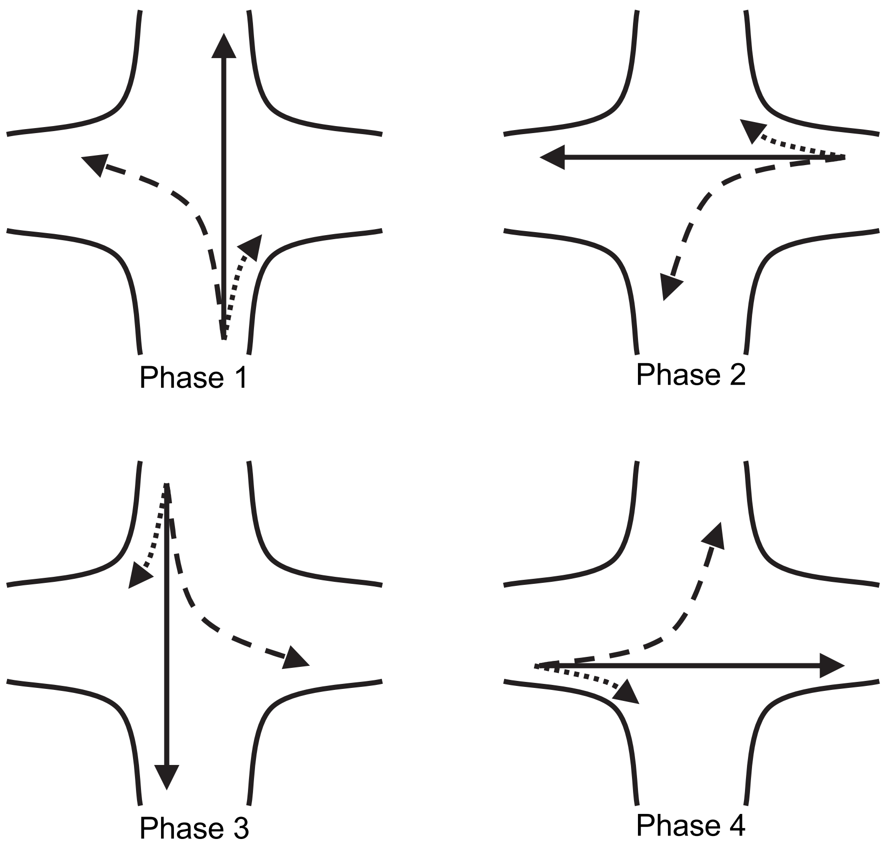

Figure 4.5 Four phase signal

If conflicts within one phase are not accepted (i.e. all movements are protected) and every incoming link is controlled separately, the number of phases is equal to the number of incoming links (see figure 4.5). These incoming links have to divide the total available capacity of that intersection. Note that the division of the available average outflow capacity of an intersection is of interest and it is assumed that the resulting division of capacities after optimization can be translated into realistic signal plans. However, this also means that it is not possible to control one single direction, which is mainly relevant to meter a specific direction for which the length of the dedicated turning lane is large enough. This means that the focus is on strategies that meter or give way per incoming link.

Assuming all incoming links to have a single lane with the same characteristics, the easiest way to determine the total capacity of the intersection is by the number of vehicles that can pass the intersection from one direction if the signal for this direction were always green. In that case the total capacity equals the capacity q_{ac} of one incoming link. The total capacity of an intersection actually depends also on the total lost times (as a result of all red time and start up lost time), number of dedicated turning lanes, number of heavy vehicles, road gradient, parking facilities next to the road, possible stops of busses, right and left turning traffic and the presence of conflicting pedestrian and bicycle flow. (TRB, 2000). The number of heavy vehicles, road gradient, parking facilities next to the road, possible stops of busses, right and left turning traffic and the presence of conflicting pedestrian and bicycle flow is not addressed, assuming that the influences of these aspects are already incorporated in the capacities q_{ac} of the incoming links. However, the total lost times influence the effective green time g_a and therefore the available outflow capacity and obviously the number of available dedicated turning lanes also influences the available capacity per incoming link q'_{ac}. The resulting outflow capacity is therefore: $q_{ao} = \alpha_a q_{ac} \beta g_a^p$, in which q_{ac} the capacity per lane, α_a the correction factor for dedicated turning lanes, β the correction factor for total lost time and g_a^p the percentage of green time given to this direction. Note that assuming 4 incoming links $a \in \{1,2,3,4\}$, means that $g_4^p = 100\% - g_1^p - g_2^p - g_3^p$. Within the optimization framework a number distributions of green times are predefined and every setting of s_b^t refers to such a setting.

The Highway Capacity Manual states that the default lost time per cycle equals 4 seconds per phase (TRB, 2000 p. 10-22). Assuming an average cycle length of 100 seconds results in a loss of capacity of 16% means $\beta = 0.86$, which is used as a default value. The correction factor for dedicated turning lanes α_a depends on the number of dedicated turning lanes l_s and the number of lanes dedicated to the major flow l_m. In the used DTA model the dedicated turning lanes are not defined, which means that if the basic number of lanes equals 2 and there are 4 dedicated turning lanes on the incoming link in reality, the incoming link only contains 2 lanes. The capacity q_{ac} is defined as the capacity per lane. However, because a total outflow capacity is used for the incoming link, this can not be equal to the capacity per lane times the number of dedicated turning lanes. If this is assumed, all lanes could be used for every direction. Therefore, the correction factor for dedicated turning lanes is defined by $\alpha_a = l_m + \gamma(l_s - l_m)$. This means that the total basic outflow capacity equals the outflow capacity of the number of lanes for the major flow plus an additional capacity as a result of the presence of dedicated turning lanes. Although this is case specific, it is assumed that the direction with the largest number of dedicated turning lanes contains the major flow and that on average $\gamma = 0.5$, which is used as a default value. This value means that half of the capacity of the additional lanes is fully used during the green time of this incoming lane. In reality this depends on the traffic flow distribution over the directions. However, these distributions are not known in advance. Note that if more traffic than capacity reserved for the other directions use these directions, the outflow capacity of the major flow is under estimated and vice versa. To avoid the need to define γ it is also possible to model each direction with a dedicated turning lane as a separate link. In this case the outflow capacity of every direction is calculated in which the effective green time of the directions connected to the same incoming link is equal and $\alpha_a = l_a$.

Using a signal plan with more than two phases means only a nominal scale can be used when representing the solution with one decision variable. Using more than one decision variable, can result in considering infeasible solutions within the optimization approach solving the MO NDP. Therefore, a further simplification of modeling traffic signals is considered by assuming phases to be connected resulting in a variant of a two phase signal plan. Assuming two phase signal plan for all intersections offers the possibility to use a single decision variable on an interval scale. For major intersections, which are often part of the considered DTM measures within the optimization process, a real two phase signal plan is not an option because of the large conflicting flows. However, it is possible to connect phases of the four signal plan assuming two phases to receive an equal amount of green time (e.g. $g_1^p = g_3^p$, and $g_2^p = g_4^p$). These two connected phases and therefore incoming links are not necessarily the opposite directions, but based on the expected largest traffic flows derived from the lane configuration of the incoming links. Default the incoming links containing the largest traffic flow are connected. This is chosen because in reality, there are more phases available in which the largest traffic flows will consume most of the available cycle time. Note that this means only strategies are considered that meter of give way to the largest traffic flows on both directions. Other possible feasible solutions are ignored.

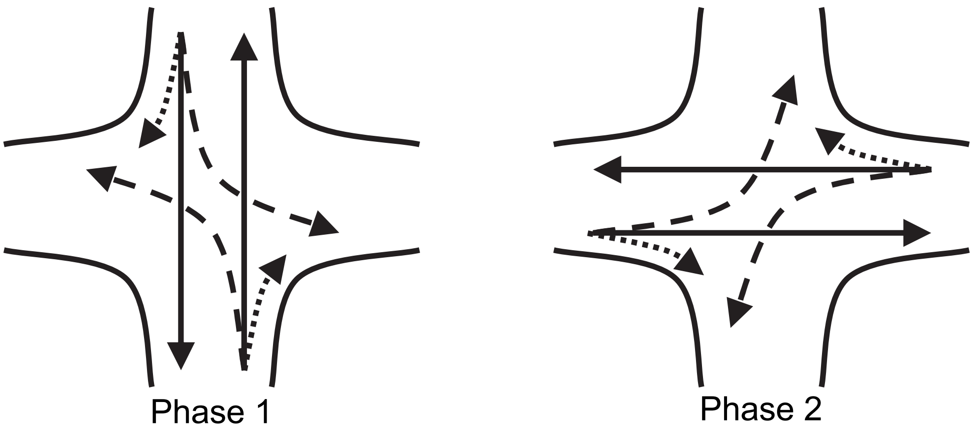

Figure 4.6 Two phase signal

For minor intersection with no dedicated turning lanes an actual two phase signal can be defined (see figure 4.6). In this situation total green time or capacity is divided over these two phases. This means that an increase of the outflow capacity of the directions connected to a phase, increasing green time of that phase, the outflow capacity of the other directions is proportionally lowered. In this signal plan two incoming links (for a four–way intersection) are connected to one phase. Obviously, the remaining two incoming links are connected to the other phase. In this case the formula for the outflow capacity $q_{ao} = \alpha_a q_{ac} \beta g_a^p$, holds. However, in this case the correction factor α_a depends on the number of vehicles turning left and right, which is case specific (see e.g. TRB, 2000). In these situations an average effect of these vehicle movements is used to set α_a.

4.4.3 Modeling of variable lane configuration

The variable lane configuration is modeled using the variables number of lanes l, capacity (per lane) q_c and depending of measure also free speed v_f and speed at capacity v_c. The HCM (TRB, 2000) uses a default capacity per lane depending on the interchange spacing, which means that doubling the number of lanes automatically results in doubling capacity. For the Dutch situation the capacities reported in “Capaciteitswaarden Infrastructuur Autosnelwegen” (AVV, 1999) does not show this linear relation. Here it is found that there is mainly a significant increase in capacity per lane comparing a road with two or three lanes. However, most DTM measures that can be distinguished using a variable lane configuration are not in accordance with the ‘normal’ lane design. Examples of measures are rush hour lanes, tidal flow, lane closure, dynamic lane marking and buffering, see figure 4.7. A rush hour lane using the shoulder lane, affects the capacity for example and is often combined with a lower speed limit.

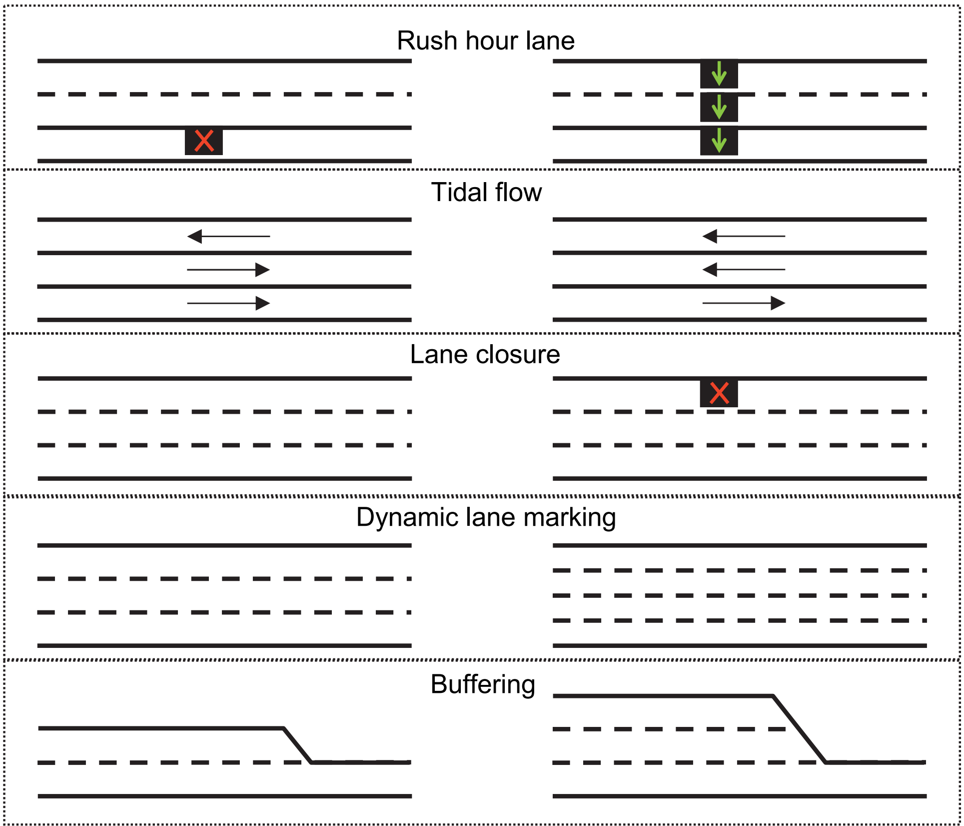

Figure 4.7 Examples of dynamic lane configuration

4.4.4 Modeling of variable speed limit

By modeling the DTM measures using the link characteristics, the variable speed limit (VSL) is modeled using the variables free speed v_f, speed at capacity v_c and capacity (per lane) q_c. In Carlson et al. (2010) the effect of VSL at motorway networks, which is reported in Papageorgiou et al. (2008), is translated in the effect it has on at the fundamental diagram. They formulated the impact of VSL at the link characteristics relative to the basic settings. The VSL value e is the ratio of the adjusted speed limit by VSL and the basic speed limit, assuming $e<1$. Lowering the speed limit, for the uncongested part of the fundamental diagram, obviously results in decreasing the slope of the flow-density curve. They also found that lower VSL values shifted the critical density k_c to higher values. In their work they found for some locations an increase of capacity for some VSL values, while for other locations no capacity increase was observed for any VSL value. Papamichail et al. (2008) for example focuses on the effect of VSL in which for higher VSL values (but lower than 1.0) an increase of capacity is found. Also in Dutch evaluation studies it is found that the effects can lead to a slightly higher as well as lower capacity (AVV, 2006). Point of attention is that the high level of speed enforcement was indicated as an important reason for finding lower capacities. The HCM (TRB, 2000) states that capacities decrease for static speed limits (reduction of 50 pcu/h/ln for a decrease of 5 mi/h). For static speed limits it can be expected that the road design is accordingly, while in the dynamic variant the road design is suited to the base characteristics. This means that lowering the speed limit could result in an increase in capacity.

Independently whether capacity is increased, sufficiently low VSL values lead to accordingly lower capacity. Given the results presented in Papamichail et al. (2008) it can be assumed that a possible capacity increase can be found for speed limits between the basic speed limit and the speed at capacity and a speed limit below the speed at capacity will lead to a lower capacity. Although using the VSL is a possible measure to meter traffic for which the work of Carlson et al. (2010) provide possible settings for the link characteristics, this research, reported in this thesis, focuses on using the VSL in which the speed limit is higher than or equal to the speed at capacity. In the presented framework the VSL is modeled by changing the link characteristic free speed v_f for those modes affected. In this research it is assumed that the speed at capacity v_c stays the same (except when the speed limit is set exactly at the base speed at capacity, because of modeling properties), and capacity to be equal or depending on the situation to be slightly increased when the speed limit is lowered. In figure 4.8 the effect on the fundamental diagram is shown of lowering the speed limit, while assuming equal capacity q_c and critical density k_c.

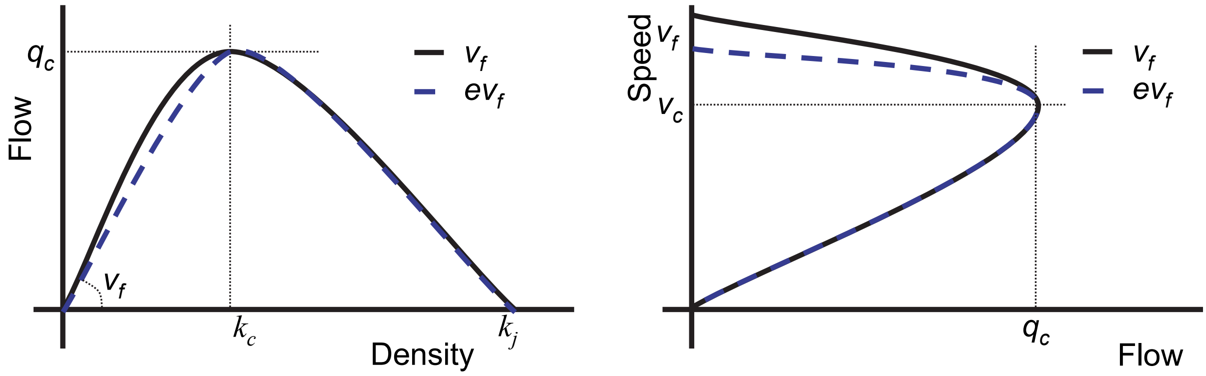

Figure 4.8 Fundamental diagrams for base conditions and VSL value e

4.5 Cases

In Chapter 5 and 6 cases are used to test various methods, which are also used in Chapter 7. Therefore, these cases are introduced in this section.

4.5.1 Case 1: Synthetic network

For providing a clear demonstration, a simple transport network is hypothesized, consisting of a single origin-destination relation with three alternative routes (see Figure 4.9). The distance between the origin and destination is approximately 25 km. One route runs straight through a city with urban roads (speed limit of 50 km/h); the second route is via a ring road using a rural road (speed limit of 80 km/h); the third route is an outer ring road via a highway (speed limit of 120 km/h). Travel demand varies with time over the simulation period. A three-hour morning peak was simulated between 6am and 9am. The travel demand (maximum of 6,300 pcu/h in the morning peak) consists of passenger cars and trucks (10% of total demand). Within the network, there are three measures available, namely two traffic lights and a VMS used to change speed limits (VSL). Solving the UE problem for this network takes approximately one minute on a single fast computer. Although the network is small, it incorporates important elements also found in real networks like urban and non-urban routes when using DTM measures to optimize the externalities.

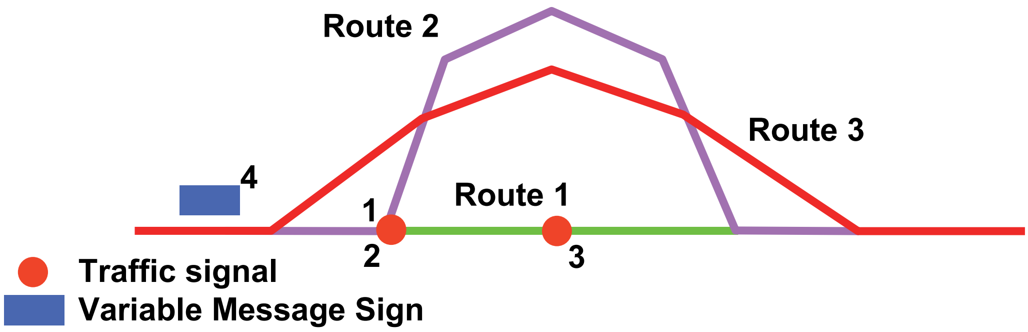

Figure 4.9 Network case 1, synthetic network (numbering measures inclusive)

Within the network (see Figure 4.9), there are three measures available, namely two traffic lights and a VMS used to change speed limits (VSL). The VSL is modeled by changing the free flow speed and capacity (presented as an increase of the link capacity without any DTM measures C_0) on the entire highway. The first traffic light is split into two measures to define the decision variables, because the two signaled directions are in this case independent. This means the need to define γ was avoided by modeling each direction with a dedicated turning lane as a separate link. The traffic lights are modeled by influencing the outflow capacity q_o of the link. In total six time intervals for the DTM measures are distinguished, equally divided into 30 minute slices, which means $t \in \{1,...,6\}$. The possible settings s_b^t, and ways these are modeled by changing link characteristics, are given in Table 4.4. Note that only the changes in settings are presented for those links affected by the measure. In this case no extreme settings are considered (e.g. rigorous lowering of speed limits or capacities). The total number of feasible solutions amounts to 4.05×10^{21}.

Table 4.4 Overview modeling DTM measures case 1

Measure	s_b^t	**Characteristic**	$C(s_b^t)$	C_0
Traffic light 1	$s_1^t \in \{1,...,11\}$	q_o	$C(s_1^t) \in \{500,600,...,1400,1500\}$	$C_0 = 1000$
	$s_2^t \in \{1,...,11\}$	q_o	$C(s_2^t) \in \{500,600,...,1400,1500\}$	$C_0 = 1000$
Traffic light 2	$s_3^t \in \{1,...,11\}$	q_o	$C(s_3^t) \in \{500,600,...,1400,1500\}$	$C_0 = 1000$
VSL	$s_4^t \in \{1,...,3\}$	$\begin{pmatrix} v_f \\ v_c \\ \text{increase } q_c \end{pmatrix}$	$C(s_4^t) \in \left\{ \begin{matrix} 80 & 100 & 120 \\ 75 & 80 & 80 \\ 0.05 & 0.025 & 0 \end{matrix} \right\}$	$C_0 = \begin{pmatrix} 120 \\ 80 \\ 0 \end{pmatrix}$

4.5.2 Case 2: Almelo

A realistic network of the city of Almelo, situated in the eastern part of the Netherlands, is used as second case. Within this case the main roads are modeled, resulting in a network consisting of 636 links and 257 nodes. The model has been extracted from a calibrated larger model of the Twente Region. The city has two entrances via the highway, but most of the radial roads are also important routes to the city, facilitating regional traffic. A three-hour morning peak is simulated and the used OD-matrix is manipulated to increase congestion problems to a more challenging level. The total travel demand amounts to 45,218 vehicles, differentiated between passenger cars and trucks. Within this case seven traffic signals and 2 VMSs (to change the speed limit, VSL) are available. These traffic signals are chosen, because these are the main entrances to the city and the VMSs are chosen, because with this measure traffic using the two entrances via the highway can be influenced. Solving the UE problem for this network takes approximately 15 minutes on a single fast computer.

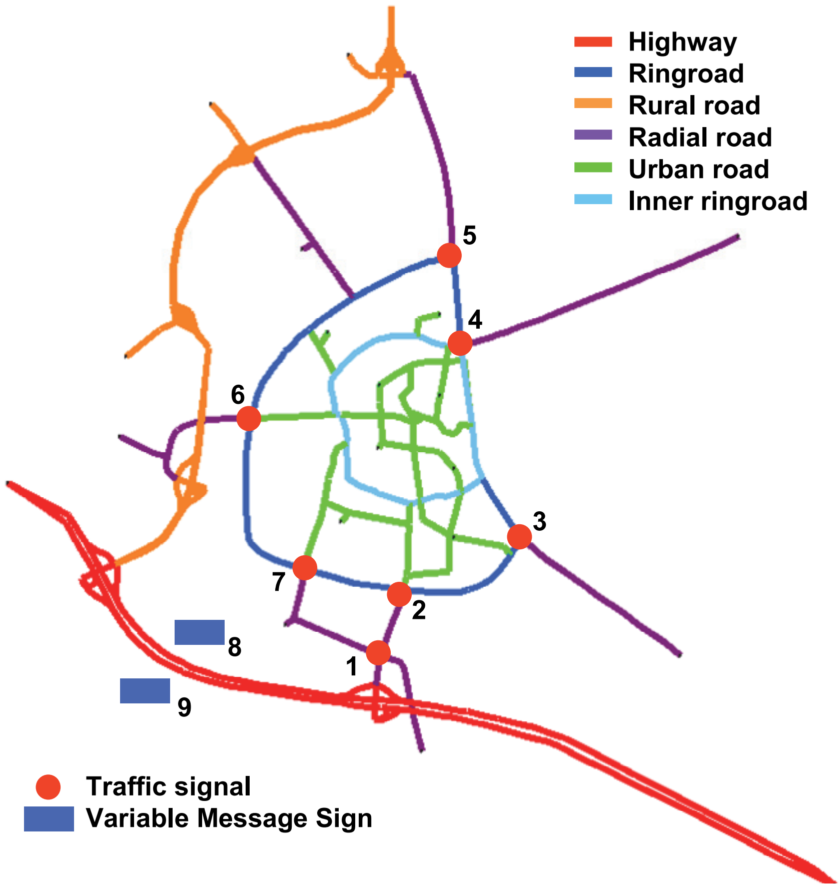

Figure 4.10 Network case 2, city of Almelo (numbering measures inclusive)

Within this case nine DTM measures are available as shown in Figure 4.10. Each of the seven traffic signals distinguishes nine predefined settings and the two VMSs (to change the speed limit, VSL) three different settings. In total, six time intervals for the DTM measures are distinguished, equally divided into 30 minute slices, which means $t \in \{1,...,6\}$. The possible settings s_b^t, and ways these are modeled by changing link characteristics, are given in Table 4.5. Note that only the changes in settings are presented for those links affected by the measure. The traffic signals are all situated on major intersections and by connecting phases of the four signal plan, like explained earlier, still a single decision variable on an interval scale can be used. In this case it is assumed that two phases receive an equal amount of green time (e.g. $g_1^p = g_3^p$, and $g_2^p = g_4^p$). These two connected phases and therefore incoming links are not necessarily the opposite directions, but based on the expected largest traffic flows, derived from the lane configuration of the incoming links. To determine the final settings, the default parameter settings for β ($\beta = 0.86$) and γ ($\gamma = 0.5$) were used. To maintain realism, but also to avoid grid locks, a total blockage of a route by setting the outflow capacity on zero is not taken into consideration. For all traffic signals the interval of possible settings is based on the traffic flows according a static user equilibrium traffic assignment, in which the settings, which fitted these flows the best, are situated in the middle (i.e. $s_b^t = 5$) and it is assumed that the interval between minimum outflow capacity and maximum outflow capacity is approximately 50% more or less than this setting. This means that also in this case no extreme settings are considered. As a consequence, the feasible set contains 6.36×10^{45} possible solutions.

Table 4.5 Overview modeling DTM measures case 2

Measure	s_b^t	**Characteristic**	$C(s_b^t)$
Traffic light 1	$s_1^t \in \{1,...,9\}$	$\begin{pmatrix} q_{1o} \\ q_{2o} \\ q_{3o} \\ q_{4o} \end{pmatrix}$	$C(s_1^t) \in \begin{Bmatrix} 387 & 464 & ... & 929 & 1006 \\ 1742 & 1625 & ... & 929 & 813 \\ 108 & 129 & ... & 258 & 280 \\ 1742 & 1625 & ... & 929 & 813 \end{Bmatrix}$
Traffic light 2	$s_2^t \in \{1,...,9\}$	$\begin{pmatrix} q_{5o} \\ q_{6o} \\ q_{7o} \\ q_{8o} \end{pmatrix}$	$C(s_2^t) \in \begin{Bmatrix} 484 & 581 & ... & 1161 & 1258 \\ 2322 & 2167 & ... & 1238 & 1084 \\ 581 & 697 & ... & 1393 & 1509 \\ 1451 & 1355 & ... & 774 & 677 \end{Bmatrix}$
Traffic light 3	$s_3^t \in \{1,...,9\}$	$\begin{pmatrix} q_{9o} \\ q_{10o} \\ q_{11o} \end{pmatrix}$	$C(s_3^t) \in \begin{Bmatrix} 387 & 464 & ... & 929 & 1006 \\ 1161 & 1084 & ... & 619 & 542 \\ 1161 & 1084 & ... & 619 & 542 \end{Bmatrix}$
Traffic light 4	$s_4^t \in \{1,...,9\}$	$\begin{pmatrix} q_{21o} \\ q_{22o} \\ q_{23o} \\ q_{24o} \end{pmatrix}$	$C(s_4^t) \in \begin{Bmatrix} 774 & 851 & ... & 1316 & 1393 \\ 968 & 871 & ... & 290 & 193 \\ 774 & 851 & ... & 1316 & 1393 \\ 968 & 871 & ... & 290 & 193 \end{Bmatrix}$
Traffic light 5	$s_5^t \in \{1,...,9\}$	$\begin{pmatrix} q_{25o} \\ q_{26o} \\ q_{27o} \end{pmatrix}$	$C(s_5^t) \in \begin{Bmatrix} 310 & 387 & ... & 851 & 929 \\ 1238 & 1161 & ... & 697 & 619 \\ 310 & 387 & ... & 851 & 929 \end{Bmatrix}$
Traffic light 6	$s_6^t \in \{1,...,9\}$	$\begin{pmatrix} q_{34o} \\ q_{35o} \\ q_{36o} \\ q_{37o} \end{pmatrix}$	$C(s_6^t) \in \begin{Bmatrix} 774 & 851 & ... & 1316 & 1393 \\ 968 & 871 & ... & 290 & 193 \\ 774 & 851 & ... & 1316 & 1393 \\ 1161 & 1045 & ... & 348 & 232 \end{Bmatrix}$
Traffic light 7	$s_7^t \in \{1,...,9\}$	$\begin{pmatrix} q_{38o} \\ q_{39o} \\ q_{40o} \\ q_{41o} \end{pmatrix}$	$C(s_7^t) \in \begin{Bmatrix} 464 & 581 & ... & 1277 & 1393 \\ 688 & 645 & ... & 387 & 344 \\ 464 & 581 & ... & 1277 & 1393 \\ 688 & 645 & ... & 387 & 344 \end{Bmatrix}$
VSL 8	$s_8^t \in \{1,...,3\}$	$\begin{pmatrix} v_{af} \\ v_{ac} \end{pmatrix}, \forall a \in \{101,...,111\}$	$C(s_8^t) \in \begin{Bmatrix} 80 & 100 & 120 \\ 75 & 80 & 80 \end{Bmatrix}$
VSL 9	$s_9^t \in \{1,...,3\}$	$\begin{pmatrix} v_{af} \\ v_{ac} \end{pmatrix}, \forall a \in \{121,...,131\}$	$C(s_9^t) \in \begin{Bmatrix} 80 & 100 & 120 \\ 75 & 80 & 80 \end{Bmatrix}$

4.6 DTA modeling

The framework presented uses a DTA model to solve the lower level optimization problem (i.e. the dynamic UE problem). A DTA model is chosen, because for the optimization of DTM measures it is necessary to reckon with the deployment of these measures and the traffic dynamics when optimizing traffic systems. In addition, to assess the effects on efficiency but also on the externalities the use of a DTA model is preferred, because there is a proven relation between the traffic dynamics and external effects like emissions of pollutants and traffic safety Aarts and Van Schaagen, 2006; Boddy et al., 2005; Golob, 2004; Kuhlwein, 2004; Leclercq, 1999 and Lord, 2005). Within dynamic models a distinction can be made in macroscopic, mesoscopic and microscopic models (Hoogendoorn and Bovy, 2001). Macroscopic DTA models are usually based on hydrodynamics theories. These models use time of the day as a variable and describe traffic flows moving through a network. Mesoscopic DTA models are often based on gas-kinetics and use aggregate behavior of individual vehicles. Therefore, traffic is represented by groups of traffic entities. However, also other approaches that combine for example macroscopic behavior and microscopic representation are called mesoscopic. The basic outputs of these mesoscopic and macroscopic DTA models are flows, speeds and densities, all as functions over time and space. Microscopic DTA models describe the space-time behavior of individual vehicles as well as their interaction. Often, these models offer the possibility to define specific distributions of parameters connected with this behavior (e.g. aggression, or desired speed). These distributions are used to model individual road users (vehicle-driver combinations). The basic outputs of these microscopic DTA models are vehicle trajectories. Macroscopic and some mesoscopic models combine the advantages of static transport models (computation time and network size) and microscopic DTA models (calculation of the traffic state and modeling of dynamic/more complex measures). Because microscopic DTA models need large computational capacity (mainly because the used Monte Carlo simulation results in many runs to asses one single solution) and are therefore limited concerning the network size. Since both problems and solutions have a network wide effect, especially macroscopic DTA models are well suited to solve the lower level.

However, there are some additional traffic related requirements regarding the used DTA model concerning the dynamic network loading (DNL), route choice modeling and possibility to model DTM measures. Concerning the DNL the DTA model needs to calculate realistic speeds on all network links for different vehicle categories to assess the externalities the correct way. This means that the DTA model used, needs to model traffic phenomena like queuing, spillback and shockwaves. In addition, it needs to model multiple classes to be able to model and asses the various vehicle categories separately. Concerning route choice the DTA model needs to calculate a dynamic UE, because at the lower level of the bi-level optimization problem the route choice behavior of road users is modeled this way. To be able to model the DTM measures, the DTA model has to have the capability to model time dependent measures that influence the link characteristics. Additionally, there are some requirements regarding the use of such model within a framework in which the model is run externally (possibly distributed using multiple computer). It should therefore be easy to import and export the inputs and outputs of this model, to use within an optimization procedure.

In this research the Streamline macroscopic DTA model (Raadsen et al., 2010) is used, which is part of the OmniTRANS transport planning software package. This DTA model contains all the requirements stated above and was available for this research. Streamline is a multi-class

DTA model with physical queuing and spillback. It uses a paired combinatorial logit (PCL) model on a pre-generated route set to model route choice, and can be used to solve the dynamic UE problem. In both cases presented in Section 4.5 the (dis)utility of a route consists of travel time. Within the PCL model relative utilities are used and the route choice spread parameter is set to 0.07. The propagation model is a second order cell transmission model (CTM) based on the METANET model by Messmer and Papageorgiou (1990), but modified and extended with urban road modeling, cross node and junction modeling. The Streamline DTA model provides the possibility to change network elements (i.e. supply of infrastructure) using controls. These controls can change these characteristics depending on a certain trigger. Outputs of this DTA model are speeds, densities and flows on all links of the network as a function of time. From this, the traffic state of all network elements can be determined as a function of time. Additionally, it can be used as a black box within an optimization procedure in which importing inputs and exporting outputs is relatively easy.

4.7 Concluding remarks

This chapter provided the general framework of the MO NDP. Although the focus lies on optimization of DTM measures, this framework could also apply for other design variables (e.g. infrastructure design or road pricing). This is also the case for the solution approach, which is discussed in the next chapter. The DTM measures in this research, especially traffic signals, are modeled in a simplified way mainly to determine the service (improving throughput, metering and or buffering traffic), which is of interest on a strategic level and has the advantage of reducing the design variables. Special attention should be paid to the possible settings and possible combinations of measures in a network, acting as one. After determination of the best performing solution, the services still need to be translated to actual settings (e.g. green times) of the DTM measures.

The DTA model that is used to operationalize the lower level is of importance to assess the effects on the externalities correctly, but will increase computation time enormously and therefore emphasizes the need for possible accelerations, which is an important issue in the next chapter. Although traffic dynamics is also relevant for traffic safety, only a limited part (route choice effects) is considered in the method used to evaluate this externality. As also already concluded in chapter 3, there is still a gap in knowledge to incorporate traffic dynamics in a good way when quantifying the effects on traffic safety using traffic models. In addition, the presented framework uses objective functions expressing the network performance of the different externalities. Next to equity issues regarding accessibility, this also results in a limited view concerning the effects on the objectives noise and air quality, which are local issues. For these objectives some parameters are incorporated concerning the level of urbanization and therefore the people being confronted with certain emissions. However, setting these parameters has been done in a pragmatic way and can also be done by using e.g. more precise information on the number of people living near the different roads. In addition, DTM has been recognized as being a possible measure to help attaining the limit values related to air quality. In this research it is assumed that strategic DTM can be used to reduce emissions especially in urban regions and therefore improve livability. Although it is possible to formulate additional constraints regarding these limit values, this is not done to avoid optimization on limit values, becoming an objective itself, and possibly restricting the feasible space rigorously, resulting in useless information on possible trade-offs.

Another issue regarding the objective functions, is the assumption that these are the objectives of the joined road management authorities. In reality there are different road management authorities, who do not necessarily have the same objectives and are responsible for their own road network and the deployment of DTM measures acting on it. If these authorities would not cooperate the optimization problem should be formulated as a multiplayer MO NDP, in which the different road authorities also react on each other. In Taale (2008) this is for example used for the single objective case (optimizing efficiency) and shown that better results can be achieved if the road authorities do cooperate. Regarding the objective functions, all of these are calculated based on handling total demand on the network. This means that all vehicles have reached their destination and for example the total emissions for all solutions are based on exactly the same number of vehicles. This way it is avoided that strategies perform well that try to reduce the number of vehicles during a specific evaluation period (e.g. metering traffic rigorously when entering the network). In addition, delays and emissions of vehicles at origins that could not enter the network at the desired departure time (as a result of blocking back), have been taken into account. For noise the time period used is equal for all assessed solutions, which means also time periods are taken into consideration in which possibly no vehicles are using the road network. The reason for this is that noise is energetically averaged over time, calculating an equivalent average sound power level. The relative effects for sound energy are not influenced, however because sound power level in dB(A) uses a logarithmic scale, this does have a limited impact on the relative effects (i.e. are possibly slightly larger).

Finally, the behavioral effects as a result of the deployment of DTM measures are limited, in this research, to route choice effects and travel demand is fixed. However, in reality it is also possible that there are effects on departure time, mode choice, destination choice or trip generation. Although it is possible to incorporate these effects into the framework, these are not taken into account. First of all because extreme strategies are not considered, which means mainly route choice effects are expected. Second reason is the calculation times needed to incorporate these effect. If these effects are taken into account, the objective function regarding accessibility has to be altered and is no longer related in the same way to congestion as it is now.

Chapter 5

Solution approach

Omdat alles wat je niet oplost zoals het hoort, niet wordt opgelost
Because everything that is not solved the way it should, will not be solved
Johan Cruijff

In chapter 4 the general framework of the MO NDP is presented, in which DTM measures are the decision variables and minimizing the externalities of traffic are the objectives. The current chapter discusses the solution approach and the related challenges that were presented in Chapter 2. Multi-objective optimization, as the name suggests, deals with more than one objective function to be minimized or maximized. Traditionally, multi-objective optimization problems have been mostly solved as a single objective optimization problem, by using a weighted sum of the objectives (e.g. by monetizing the effects). However, the true outcome of a multi-objective optimization problem is a Pareto optimal set of solutions, the so-called trade-off solutions. To solve this multi-objective optimization problem, heuristics are needed. These heuristics are computationally expensive, because many possible solutions need to be assessed. In addition, the usage of a DTA model to solve the user equilibrium problem at the lower level, results already in a time-consuming task to assess one single solution. Therefore, next to a comparison of some multi-objective genetic algorithms, also approaches using approximation methods to accelerate the solution approach are tested, as well as possibilities to optimize the approach.

This chapter presents solution approaches. After presenting some background on multi-objective optimization and characteristics of the optimization problem, heuristics are presented and compared, as well as some methods to accelerate the search. These solution approaches are used in in case studies to test various pruning and ranking methods (Chapter 6) and to evaluate the outcome of an optimization (Chapter 7).

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Wismans, L. J. J., E.C. van Berkum & M. C. J. Bliemer (2012). Accelerating solving the dynamic multi-objective network design problem using response surface methods. *Journal of ITS (in press)*.

5.1 Multi-objective optimization

5.1.1 Characteristics and solutions

The MO NDP can not be solved exact without reformulation of the problem, because this bi-level optimization problem is non-convex, non-differentiable and NP-hard (Gao et al., 2005; Chiou, 2005a). Reformulation of the dynamic NDP is not an option, as discussed in Chapter 2, which means heuristics are needed to solve the MO NDP. The multi-objective nature of the problem introduces another complexity; the optimization generally results in a Pareto optimal set and not one single solution. This Pareto optimal set is potentially very large, depending on the level in which the objectives are opposed. In addition, using heuristics means that for all cases used in this research, it is uncertain if the actual Pareto optimal set is found. Heuristics generally focus on finding a subset of solutions that are non-dominated within the assessed solutions.

Heuristic optimization methods are subject to the no free lunch theorem. This theorem states that all optimization methods perform on average equally well across all classes of optimization problems. So if an algorithm A outperforms an algorithm B in one class of problems, B can outperform A in another (Wolpert and Macready, 1997; Ho and Pepyne, 2002). This means that it is useful to test several heuristics for the formulated MO NDP in this research. In bi-level multi-objective optimization studies, solution approaches using evolutionary multi-objective algorithms (EMOA), have proven to be successful (Deb, 2001; Konak et al., 2006)). GA, which are part of the class of EAs, are the most widely used heuristic also for NDP and in the available studies comparing heuristics, GA has been proven to perform best (see Chapter 2). Classical optimization methods like the weighted sum approach can at best find one Pareto optimal solution in one simulation run, while EAs can find multiple optimal solutions in one single search due to their population-based approach. More recently algorithms such as the dominance based multi-objective simulated annealing (DBMO-SA) method can find multiple solutions in one single search as well, but because of the local search used within this algorithm, it does not incorporate diversity in the search (Possel et al., 2012; Deb, 2001). In Chapter 2 it is shown that GA performs best in almost all comparison studies for NDP, which means that GA can deal with this optimization problem. It also shows that GA performs well in NDP in which DTM measures are the decision variables (e.g. Cantarella and Vitetta, 2006) and also in which externalities are the objectives (e.g. Possel et al., 2012; Xu and Chen, 2011). Many multi-objective GAs (MOGAs) have been proposed, however, strength Pareto evolutionary algorithm 2 (SPEA2) proposed by Zitzler et al. (2001), the non-dominated sorting genetic algorithm II (NSGA-II) proposed by Deb et al. (2002) and strength Pareto evolutionary algorithm 2+ (SPEA2+) proposed by Kim et al. (2004) provide excellent results compared to other proposed algorithms (Grosan and Dumitrescu, 2002; Zitzler et al., 2000). NSGA-II and SPEA2 are two well known and credible algorithms, used in many applications and tested in several comparative studies (Konak et al., 2006). Some of them are also already tested for MO NDP problems (e.g. Sharma et al., 2009; Sumalee et al., 2009; Possel et al., 2012). Although GAs have been proven to be successful for SO NDP and MO NDP, the mentioned promising algorithms are tested and compared in this research for the dynamic MO NDP.

Heuristics search for optimal solutions intelligently. However, these heuristics still need many function evaluations (i.e. one function evaluation comprises the computation of the outcome on the objectives of solutions). Because the evaluation of any possible solution requires solving the lower level, thus the application of a DTA model, computation times can become extremely large. A possible solution for accelerating the search is combining an EA with function approximation methods. Function approximation methods, are methods in which a surrogate model is estimated using known exact evaluations of solutions. This estimated surrogate model can be used in different ways within the optimization process. Research conducted by Fikse (2010) as part of this research has shown that response surface methods (RSM) show promising results. In this chapter three possible algorithms are tested using a hybrid method of GA and RSM.

5.1.2 Performance measures

The set of solutions $X^* = \{S_1^*, .., S_j^*\}$, which is the outcome of the MO NDP, consists of the Pareto optimal set. Mathematically, the concept of Pareto optimality is as follows. Assuming two solutions $S_1, S_2 \in F$, then S_1 is said to strongly dominate S_2 (also written as $S_1 \succ S_2$) if $z_i(S_1) < z_i(S_2)$ for all i. Additionally, S_1 is said to cover or weakly dominate S_2 (written as $S_1 \succeq S_2$) if $z_i(S_1) \leq z_i(S_2)$ for all i.

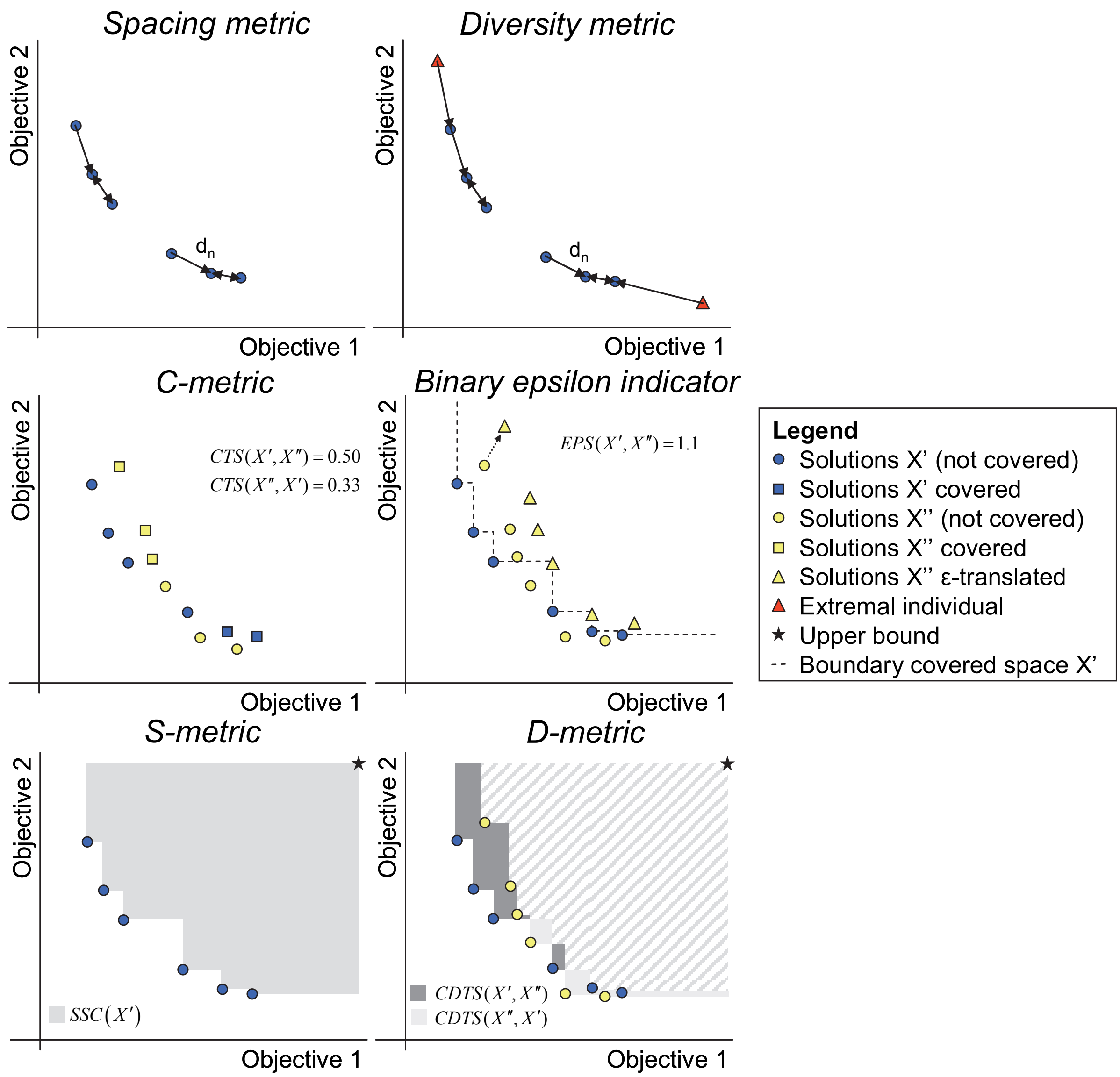

Figure 5.1 Example performance measures for bi-objective optimization problem

In order to compare the performance of MO optimization algorithms, many possible metrics are available in literature. Often used performance measures are presented in Table 5.1 and illustrated for the bi-objective case in Figure 5.1 (Deb, 2001; Zitzler et al. 2001; Zitzler et al., 2003; Grozan et al., 2003; Tan et al., 2005). These performance measures are the spacing metric, the coverage of two sets (C-metric), the size of the space coverage (S-metric), the size of the space coverage difference of two sets (D-metric), and the ratio of domination (binary epsilon-indicator). For some of them a variant is proposed that is more suitable for this research. In addition, a metric for diversity is proposed that takes into account to what extent the approach also finds the extremal individuals (containing the solutions that form the minima and maxima solutions of the individual objective functions part of the Pareto optimal set) and how well the solutions are distributed between these points. All these metrics mainly examine the performance in two aspects, i.e. the spread across the Pareto optimal front (spacing and diversity metric) and the ability to attain the global tradeoffs (C-metric, binary epsilon-indicator, S-metric and D-metric). There is no single performance measure that contains all aspect relevant for the comparison. Therefore, in the comparison of MOGA and the comparison of algorithms using RSM a combination of the presented metrics is used.

Table 5.1 Overview of performance measures used

Performance measure	**Explanation**
Spacing metric	Let $X' = (S'_1, S'_2, ..., S'_W) \subset X$ be a set of solutions. The function $SMO(X')$ determines how evenly the solutions of set X' are distributed in the objective space. Because also the distribution in the solution space is of interest, also $SMS(X')$ is defined. $SMO(X') = \frac{1}{\bar{\delta}} \sqrt{\frac{1}{W} \sum_{w=1}^{W} (\delta_w - \bar{\delta})^2}$, with $\bar{\delta} = \frac{1}{W} \sum_{w=1}^{W} \delta_n$. (5.1) δ_n is the Euclidean distance between each solution and its nearest solution. In function $SMO(X')$ this distance is measured in the objective space, while in function $SMS(X')$ this distance is measured in the solution space. The smaller the value of $SMO(X')$, the better the distribution of the solutions in X' in the objective space and the smaller the value of $SMS(X')$, the better the distribution of the solutions in X' in the solution space. The spacing metric only focuses on the spread across the solutions part of the considered set. This means that a certain set that is not near the true Pareto optimal set or only contains a specific part of this set, can still perform well on this metric.
Diversity metric	Let $X' = (S'_1, S'_2, ..., S'_W) \subset X$ be a set of solutions, and let $\hat{X} = (S^*_1, S^{\wedge}_1, ..., S^*_I, S^{\wedge}_I) \subset \tilde{X}^*$ be the set of solutions forming the extremal individuals known and $\hat{X}' = \hat{X} \cup X'$ the combination of these two sets with size $W + \xi$. Because in this case the exact Pareto optimal set is not known, $\tilde{X}^*$ is the approximated Pareto optimal set based on all evaluated solutions within all approaches. The function $DMO(\hat{X}')$ determines how evenly the solutions of set X' are distributed in the objective space between the extremal individuals. Because in this case it is not relevant to know whether this is the case in the solution space, only the objective space is considered. $DMO(\hat{X}') = \frac{1}{\bar{\delta}} \sqrt{\frac{1}{W+\xi} \sum_{w=1}^{W+\xi} (\delta_n - \bar{\delta})^2}$, with $\bar{\delta} = \frac{1}{W+\xi} \sum_{w=1}^{W+\xi} \delta_n$. (5.2) δ_n is the Euclidean distance between each solution and its nearest solution. The smaller the value of $DMO(\hat{X}')$, the better the diversity. The diversity metric focuses on the spread between the extremal individuals that form the upper and lower bounds of the approximated Pareto optimal set. This means that although a set of solutions performs well on spacing metric, it can perform poor on diversity if this set only contains a specific part of the approximated Pareto optimal set. However, a set of solutions that is not near the true Pareto optimal set, can still perform well on this metric.

C-metric	Let $X', X'' \subset X$ be two sets of solutions. The function $CTS(X', X'')$ determines the coverage of two sets of the ordered pair (X', X''), which means the level in which the solutions X' weakly dominates X''. $CTS(X', X'') = \frac{\left\|\{S'' \in X''; \exists S' \in X' : S' \succeq S''\}\right\|}{\|X''\|}$ (5.3) The value $CTS(X', X'') = 1$ means that all solutions in X'' are covered by the solutions in X'. The opposite, $CTS(X', X'') = 0$ represents the situation where none of the solutions in X'' are covered. A variant of this measure is used to determine the level of convergence, which determines to what extent the solutions X'' are equal or worse than X'. $NONDOM(X', X'') := \frac{\|X''\| - \left\|\{S'' \in X''; \exists S' \in X' : S'' \succ S'\}\right\|}{\|X''\|}$ (5.4) The value $NONDOM(X', X'') = 1$ means that there is no solution in X'' that dominates X', thus X'' is equal to or worse than X'. The C-metric focuses on the ability to attain the global trade-offs, which means that a set of solutions that dominates most of the solutions of another set found better solutions. However, this measure does not incorporate to what extent these solutions are better (i.e. are an improvement for all objectives).
Binary epsilon indicator	Let $X', X'' \subset X$ be two sets of solutions. The function $EPS(X', X'')$ determines the factor by which the solutions X' is worse than the solutions X'' with respect to all objectives. More precise, $EPS(X', X'')$ equals the minimum factor epsilon such that any of the solutions X'' is dominated by at least one of the solutions X'. $EPS(X', X'') = \inf_{\varepsilon} \{\forall S'' \in X'' \exists S' \in X' : S' \succeq_{\varepsilon} S''\}$ (5.5) The value $EPS(X', X'') = 2$ means that all solutions in X'' are covered by the solutions in X' when the objective vectors of the solutions X'' are multiplied by a factor (epsilon) of 2. If the indicator is smaller than 1 the solutions in X' have a better ability to attain the global trade-offs. This measure also incorporates to what extent this is the case. Note that it is possible that $EPS(X', X'')$ as well as $EPS(X'', X')$ can be larger than 1.
S-metric	Let $X' = (S'_1, S'_2, ..., S'_N) \subset X$ be a set of solutions. $SSC(X')$ equals the size of the space coverage. It is formed by the (hyper)volume enclosed by the union of the polytopes formed by the intersection of the following hyperplanes arising out of every single solution along with the axis in the objective space. For the minimization problem, the origin and therefore the axis are moved to a point representing the opposite of a utopian point, defined by $z^{\wedge}(z_1^{\wedge}, ..., z_I^{\wedge})$, which means the upper bound of each objective. Because the true maximum values of the objective functions are not known, a conservative point is chosen, based on the evaluated solutions. In the two-dimensional case, each polytope represents a rectangle defined by this point $z^{\wedge}$ and $(z_1(S'), z_2(S'))$. The hypervolumes are calculated based on the Hypervolume by slicing objectives (HSO) algorithm introduced by While et al. (2006). The larger the value of $SSC(X')$, the better the space coverage. The S-metric also focuses on the ability to attain the global trade-offs, which means a set of solutions performs better if its space coverage is larger. This measure does not take into account the number of solutions that are dominated. Therefore it is possible that a certain set of solutions performs better on the S-metric although most of its solutions are dominated by the other set of solutions.
D-metric	Let $X', X'' \subset X$ be two sets of solutions. The function $CDTS(X', X'')$ determines the size of the space coverage difference, which means the size of space dominated by X' and not by X'' and vice versa. $CDTS(X', X'') = SSC(X' \cup X'') - SSC(X'')$. (5.6) Using this measure assumes that, if $CDTS(X', X'') < CDTS(X'', X')$, the set of

solutions X'' is better than X'. A variant of the D-metric defined by the function $CDTS_{rel}(X',X'')$ is to normalize the D-metric using a reference hypervolume. This hypervolume in this case is defined as the hypervolume formed by point the utopian point $\hat{z}$ and a point formed by the found minima of each objective, also called the Ideal objective vector defined by $z^* = \left(z_1^*,...,z_I^*\right)$.

$$CDTS_{rel}(X',X'') = \frac{CDTS(X',X'')}{SSC(z^*)} \quad (5.7)$$

Note that there are multiple solutions forming the ideal objective vector if X' contains more than one solutions, which means that in that case z^* is a hypothetical point. The D-metric combines the C-metric and S-metric in the sense that this metric incorporates to what extent the solutions that dominate are better. The D-metric provides for example information when the C-metric results in equal performance, but by its (relative) size also information to what extent the sets of solutions form a different front. However, also for this measure it is possible that a certain set of solutions performs better on the D-metric although most of its solutions are dominated by the other set of solutions.

5.2 Evolutionary multi-objective algorithms

5.2.1 Algorithms

EA are inspired on the process of natural evolution, and are important tools for several real-world applications. GA belongs to this larger class of EA and the algorithms discussed here are all GA. These algorithms use a set of solutions (population) to converge to the optimal design. Within their search they use some fitness function to determine the performance of the different solutions, which is used within a selection process of parents that have a higher chance of survival and reproduction. The solutions also need some kind of genetic representation, the solution is a chromosome and the decision variables it contains, the genes. For reproduction, genetic operators like recombination and mutation are used. There are six steps that can be distinguished, initialization, fitness assignment, environmental selection, termination, mating selection and variation (see Figure 5.2). Within the initialization step the initial population is selected and after that the evolution happens in generation (iterative procedure). The fitness assignment determines the performance of the different solutions. Within multi-objective algorithms this fitness depends on the level in which a solution dominates other solutions. The environmental selection procedure is used to select the mating pool and to maintain a reasonable sized archive. This selection procedure is often a deterministic step, only selecting the best solutions according to their fitness value thus far, often also called elitism. If the termination conditions are not yet reached, the parents are selected in the mating selection to reproduce children. The termination conditions can be a maximum number of generations, or the level of convergence (i.e. level in which the Pareto optimal set changes). To evaluate this, the performance measures presented earlier in this chapter can be used. The reproduction is done in the variation step in which the genes of the selected parents are recombined. Within the variation often also additional genetic operators like mutation are used, which changes the genes of the produced children at random. These optimization methods are robust, do not require gradients of the objective function, can handle noisy objective functions, and they can avoid premature convergence to local optima.

All three assessed algorithms (i.e. NSGAII, SPEA2 and SPEA2+) contain elitism, which means preservation of good solutions, and use some kind of fitness sharing, which is a niching technique, to maintain population diversity. The preservation of good solutions in all approaches is guaranteed by the environmental selection step, which is a deterministic step in which an archive is maintained containing the best solutions. The number of solutions contained in the archive is constant over time, which means that if the number of non-dominated solutions is smaller than the archive size, the archive is filled with the best dominated solutions and if the number of non-dominated solutions is larger than the archive size the archive only contains the best non-dominated solutions. In the latter case mainly the influence of fitness sharing is decisive for the solutions selected for the archive.

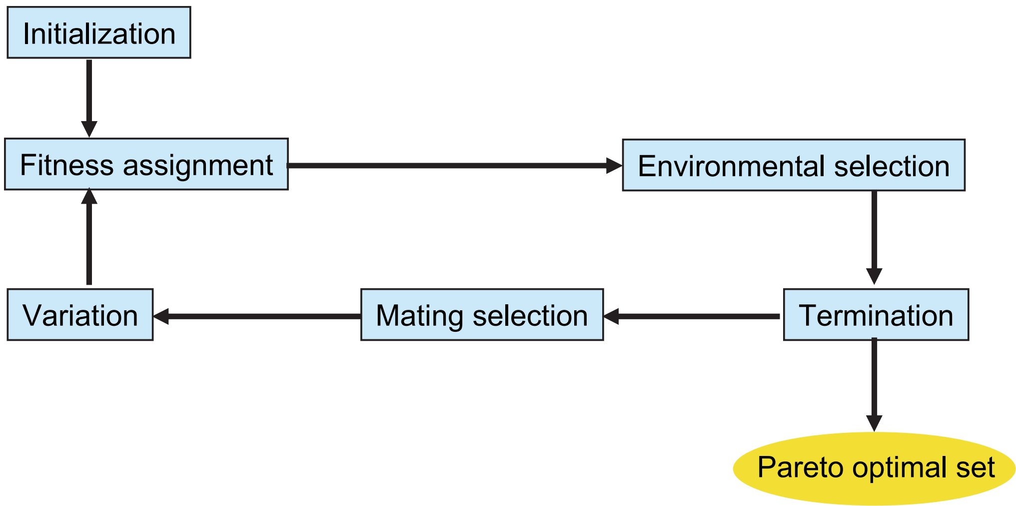

Figure 5.2 Standard procedure algorithms

Non-dominated Sorting Genetic Algorithm II (NSGAII)
Deb et al. (2002) developed an approach called non-dominated sorting genetic algorithm II (NSGAII). Within the algorithm the fitness assignment is carried out in two steps. In the first step, called non-dominance sorting, the solutions are ranked based on Pareto dominance. This is determined by setting the rank of non-dominated solutions as rank 1, extract these solutions from the total set, and select from the remaining solutions again those non-dominated solutions and set those as rank 2, etc. The second step is sorting the solutions within a certain rank by using a crowded distance measure, which means sorting based on diversity in which solutions in a highly populated area will be assigned a lower fitness within its rank. The crowded distance is a measure that is determined by the distances between the neighbor solutions of the assessed solution in the objective space and the way fitness sharing is designed. The preservation of good solutions is done by the environmental selection step in which an archive is maintained containing the best solutions considered so far, based on their Pareto dominance, and if necessary their crowded distance sorting. This archive contains the solutions used for the mating selection, which is done using binary tournament selection with replacement (i.e. parents selected for current tournament are candidates for other tournaments).

The algorithm in steps, for more information, see Deb et al. (2002) and Deb (2001):

Step 1: *Initialization*: Set population size W_p, which is equal to the archive size W_u, the maximum number of generations H, and generate an initial population U_0. Set $h = 0$ and $Q_0 = \varnothing$.

Step 2: *Fitness assignment*: Combine archive U_h and children Q_h, forming $Y_h = U_h \cup Q_h$ and calculate fitness values of solutions by dominance ranking and crowded distance sorting.

Step 3: *Environmental selection*: Determine new archive U_{h+1} by selecting the W_u best solutions out of Y_h based on their fitness.

Step 4: *Termination*: If $h \geq H$ or another stopping criteria is satisfied, then set X^* to the set of solutions part of U_{h+1} with dominance rank 1 (non-dominated solutions) and determine the size of non-dominated solutions *W*, note that $W \leq W_u$.
Step 5: *Mating selection*: Perform binary tournament selection with replacement on U_{h+1} to determine mating pool of parents P_{h+1}.
Step 6: *Variation*: Apply recombination and mutation operators to the mating pool P_{h+1} to create offspring Q_{h+1}. Set $h = h+1$ and go to step 2.

Strength Pareto Evolutionary Algorithm 2 (SPEA2)
Zitzler et al. (2001) developed the approach called strength Pareto evolutionary algorithm 2 (SPEA2). Within the algorithm, the fitness assignment is carried out in three steps. First, the strength of each solution is determined, representing the number of solutions it dominates. Secondly, the raw fitness of each solution is determined by summation of the strengths of its dominators. Thirdly, determination of the fitness by incorporation of density information in the raw fitness value, which assigns a lower fitness to solutions in a highly populated area. The density of a solution is measured in the objective space as a decreasing function of the distance to the k-th nearest neighbor. This density information forms the way fitness sharing is designed. The preservation of good solutions is done by the environmental selection step, in which an archive is maintained containing the best solutions, based on their fitness, considered so far. Within the SPEA2 approach, an archive truncation procedure is used if the size of the non-dominated solutions exceeds the archive size. This procedure iteratively removes individuals from the non-dominated solutions based on the distances between the solutions in the objective space, until the size of the non-dominated solutions equals the archive size. The method used is different from the niching method used to determine the fitness value. In the truncation procedure, the solution that has the minimum distance to another solution is chosen for removal and if there are several solutions with minimum distance the tie is broken by considering the second smallest distances and so on. This archive contains solutions used for the mating selection, which is done using binary tournament selection with replacement.

The algorithm in steps, for more information, see Zitzler et al. (2001):
Step 1: *Initialization*: Set population size W_p, archive size W_u, the maximum number of generations *H*, and generate an initial population U_0. Set $h = 0$ and $Q_0 = \varnothing$.
Step 2: *Fitness assignment*: Combine archive U_h and children Q_h, forming $Y_h = U_h \bigcup Q_h$ and calculate fitness values of solutions by strength values and density information.
Step 3: *Environmental selection*: Copy all non-dominated solutions in Y_h to new archive U_{h+1}. If the size of U_{h+1} exceeds W_u, then reduce U_{h+1} by truncation, otherwise if less than W_u, then fill U_{h+1} with best solutions out of Y_h based on their fitness.
Step 4: *Termination*: If $h \geq H$ or another stopping criteria is satisfied, then set X^* to the set of solutions part of U_{h+1} with fitness value smaller than 1 (non-dominated solutions) and determine the size of non-dominated solutions *W*, note that $W \leq W_u$.
Step 5: *Mating selection*: Perform binary tournament selection with replacement on U_{h+1} to determine mating pool of parents P_{h+1} of size W_p.
Step 6: *Variation*: Apply recombination and mutation operators to the mating pool P_{h+1} to create offspring Q_{h+1}. Set $h = h+1$ and go to step 2.

Strength Pareto Evolutionary Algorithm 2+ (SPEA2+)
Kim et al. (2004) adapted the SPEA2 approach, as they argued that the crossover mechanism within NSGAII and SPEA2 had not yet explored and both lack maintaining diversity in the solution space, because fitness sharing is performed using information on the objective space.

The SPEA2+ approach differs in three ways of the SPEA2 approach. First, it uses neighborhood crossover, which crosses over solutions close to each other in the objective space. Secondly, within the mating selection, all solutions within the archive are selected as parents. Thirdly, maintaining two archives in which in case of the truncation procedure in one archive, truncation is done by using the distances within the objective space and in the other archive in the solution space.

The algorithm in steps, for more information, see to Kim et al. (2004):

Step 1: *Initialization*: Set population size W_p, which is equal to the archive size W_u, the maximum number of generations *H*, and generate an initial population OU_0. Set $h = 0$, $DU_0 = \varnothing$ and $Q_0 = \varnothing$.

Step 2: *Fitness assignment*: Combine archive OU_h, DU_h, and children Q_h, forming $Y_u = OU_h \cup DU_h \cup Q_h$, and calculate fitness values of solutions by strength values and density information.

Step 3: *Environmental selection*: Copy al non-dominated solutions in Y_h to new archives OU_{h+1} and DU_{h+1}. If size of OU_{h+1} and DU_{h+1} exceeds W_u, then reduce OU_{h+1} by truncation using distances in the objective space and DU_{h+1} by truncation using distances in the solution space, otherwise if less than W_u, then fill OU_{h+1} and DU_{h+1} with best solutions out of Y_h based on their fitnesses.

Step 4: *Termination*: If $h \geq H$ or another stopping criteria is satisfied, then set X^* to the set of solutions part of DU_{h+1} with fitness value smaller than 1 (non-dominated solutions) and determine the size of non-dominated solutions *W*, note that $W \leq W_u$.

Step 5: *Mating selection*: If truncation procedure is used, select DU_{h+1} as mating pool of parents P_{h+1}, otherwise if not, select OU_{h+1} as mating pool of parents P_{h+1}.

Step 6: *Variation*: Apply neighborhood crossover and mutation operators to the mating pool P_{h+1} to create offspring Q_{h+1}. Set $h = h+1$ and go to step 2.

Additional settings

All algorithms need some kind of genetic representation. In this research the solution vector as described in chapter 4 is used. This means that the integers describing the settings of the DTM measures for the different time intervals are used $S = \{s_b^t, \forall t = 1,...,T, \forall b = 1,...,B\}$. When there are nine DTM measures and six time periods, the chromosome describing one solution contains 54 genes. For all algorithms the same genetic operators are used, namely uniform crossover with a recombination rate ρ_{rec} of 1, which means all selected parents are recombined, and mutation in which the mutation rate ρ_{mut} can change over generations. Only small mutations occur, as it is assumed that mutation results in shifting the DTM application one up or down, i.e., if s_b^t is selected for mutation, its value after mutation becomes either $s_b^t - 1$ or $s_b^t + 1$. To avoid the production of infeasible solutions (i.e. $s_b^t < 1 \vee s_b^t > M_b$, as a result of mutation, the direction of mutation is changed if this occurs (e.g. $s_b^t - 1$ becomes $s_b^t + 1$ when $s_b^t - 1 \notin \{1,...,M_b\}$. As a result of this representation and the used genetic operators, the algorithm does not produce infeasible solutions (i.e. constraints are never violated), which avoids assessing infeasible solutions or the need for repair procedures.

5.2.2 Comparison algorithms

Set up comparison algorithms

To compare the algorithms, case 1, which is described in Chapter 4, and a selection of the objectives, namely efficiency, climate and noise is used. This case has the advantage of relative limited time needed to solve the lower level and it incorporates important elements like urban and non-urban routes, which is representative for real networks. Because the algorithms are computationally expensive, mainly due to solving the lower level, the performance of the algorithms is of interest when the computation time is restricted (i.e. is an algorithm capable of finding already good solutions in the first iterations). Therefore, the number of solutions that can be considered is limited in the comparison. In the comparison of the algorithms, the total number of solutions evaluated after the initialization is a fixed number of 5,000 solutions. For all algorithms the population size W_p is varied, 50 or 100 solutions, the archive size is chosen to be equal to this population size (i.e. $W_u = W_p$) and the initial mutation probability is varied ρ_{mut}^{init}, 0.2 or 0.05, which decreased every generation with 5% for the first 10 generations. This results in 12 different approaches in total. Because GAs are stochastic in nature, all approaches were carried out 5 times. On a single fast computer, all these computations would take approximately 8 months, hence the computations were distributed over multiple computers. For obtaining more information about the level of convergence, all algorithms are also applied in which after the initialization a fixed number of 10,000 solutions are considered, which means doubling of the terminal generation.

Results convergence
All results are presented in Table 5.2. The average development of the performance metrics of the three approaches with different population sizes and initial mutation probabilities are analyzed during the generations. Because the population sizes are different and a fixed number of solutions are considered, the performance is averaged based on an equal number of solutions evaluated. This means it is the average performance of all three approaches after a certain number of solutions compared with a base case. The average results after 5,000 solutions are used as the base case. On average, the space coverage after 10,000 solutions is 1.2% larger than after 5,000 solutions, while in comparison to 1,000 solutions the space coverage is 4.2% lower and versus the starting population, not shown in Table 5.2, 20%.

Table 5.2 Overview results convergence

	After *n* solutions			
Measure	**n=1,000**	**n=2,500**	**n=7,500**	**n=10,000**
S-metric SSC(n)/SSC(5000)	-4.2%	-1.5%	0.7%	1.2%
Spacing metric SMO(n)/SMO(5000)	66.7%	6.5%	-0.5%	-7.3%
Spacing metric SMS(n)/SMS(5000)	1.4%	-4.5%	12.2%	1.3%
Diversity metric DMO(n)/DMO(5000)	18.1%	5.9%	-7.9%	-8.7%
C-metric CTS(5000,n)	44.3%	26.4%	13.8%	11.8%
C-metric CTS(n,5000)	3.5%	10.8%	20.3%	18.7%
C-metric NONDOM(5000,n)	96.8%	93.7%	86.2%	85.5%
C-metric NONDOM(n,5000)	57.8%	77.1%	91.7%	91.3%
D-metric $CDTS_{rel}(5000,n)$	4.0%	1.6%	0.3%	0.3%
D-metric $CDTS_{rel}(n,5000)$	0.1%	0.2%	0.9%	1.3%

The spacing metric shows that after 10,000 solutions, this measure is on average 7.3% lower for the objective space and 1.3% higher for the solution space compared to 5,000 solutions. The comparison of 5,000 versus 1,000 solutions shows on average 67% higher values for the objective space and 1% higher values for the solution space. However, the results on this measure are diverse for the different approaches (e.g., there are approaches for which the spacing metric deteriorates after 10,000 solutions compared to 5,000 solutions), which can be explained because the spacing metric only determines how evenly the points of the non-dominated solutions found thus far, are distributed. Finding for example new extremes in next generations, in combination with the truncation procedure possibly carried out in earlier generations, can result in less diversity according to the spacing metric. Additionally, since the decision variables are discrete, not knowing the exact Pareto optimal set, it is not possible to conclude, based on these spacing metric results, whether the approaches have converged.

The diversity metric in which the spacing metric is normalized using the extremal solutions, shows as expected a more stable development in the outcome of the metric when the number of solutions increases. The results of this metric show that after 10,000 solutions the measure is on average 9% lower compared to 5,000 solutions, and after 1,000 solutions 18% higher. This means that after 5,000 solutions, there are improvements possible concerning the spread across the Pareto optimal front.

The C-metric *CTS* shows that after 1,000 solutions, 3.5% of the solutions part of the set are dominating or equal to the solutions part of the set after 5,000 solutions and 44,3% of the solutions part of the set after 1,000 solutions are dominated or equal to the solutions part of the set after 5,000 solutions. After 10,000 solutions, the results are 18,7% and 11,8%, which means that after 5,000 solutions the algorithms already found reasonable results. This is also shown by the *NONDOM* measure, which shows that after 10,000 solutions, on average 14.5% of the solutions part of the set found after 5,000 solutions are dominated. However, also 8.7% of these solutions are dominated by the set found after 5,000 solutions. This is possible, because as a result of the truncation procedure also non-dominated solutions are removed from the set in the environmental selection step, when the number of non-dominated solutions exceeds the archive size. The D-metric shows that the relative size of the space covered only by the set after 5,000 solutions is 4.0%, while this is 0.1% for the set after 1,000 solutions. After 10,000 solutions, the resulting set covers 1.3% more space, while this is 0.3% for the set after 5,000 solutions.

The different metrics show that there are still improvements possible after 5,000 solutions. However, for some metrics these improvements are relatively low. Because it is of interest of finding good solutions in limited time, the comparison between the individual algorithms and parameter settings focuses on the performance of the algorithms after 5,000 solutions.

Results comparison NSGAII, SPEA2 and SPEA2+
Table 5.3 shows the average results of the spacing metric, diversity metric and S-metric.

Table 5.3 Overview results spacing, diversity and space coverage

	Population size	Mutation rate	Spacing metric solution space	Spacing metric objective space	Diversity metric	S-metric
NSGAII	100	0.20	0.32	0.72	3.02	2.03E+11
	100	0.05	0.35	0.79	2.09	2.03E+11
	50	0.20	0.43	0.68	1.57	2.01E+11
	50	0.05	0.43	0.77	1.62	2.04E+11
Average			**0.38**	**0.74**	**2.08**	**2.03E+11**
SPEA2	100	0.20	0.28	0.37	1.83	2.02E+11
	100	0.05	0.24	0.40	1.61	1.98E+11
	50	0.20	0.31	0.24	1.57	2.02E+11
	50	0.05	0.31	0.24	1.30	2.01E+11
Average			**0.29**	**0.31**	**1.58**	**2.00E+11**
SPEA2+	100	0.20	0.21	0.39	1.85	2.06E+11
	100	0.05	0.20	0.27	1.65	2.03E+11
	50	0.20	0.26	0.20	1.09	2.01E+11
	50	0.05	0.24	0.23	1.09	2.01E+11
Average			**0.22**	**0.27**	**1.42**	**2.02E+11**

The SPEA2 and SPEA2+ algorithms perform better than the NSGAII algorithm concerning the spacing metric in the solution space as well as in the objective space. As expected, SPEA2+ performs best, while this approach uses also diversity in the solution space within the environmental selection step. The S-metric shows that on average the NSGAII and SPEA2+ approach perform slightly better than the SPEA2 approach. Concerning the population size, the spacing and diversity metric in the objective space show better results when the population size is 50 compared to 100 solutions and slightly worse concerning the S-metric. This can be explained because the population size is smaller, the number of generations is higher and the impact of fitness sharing in the algorithms is larger. However, a smaller population size will automatically result in a smaller S-metric when the solutions of both algorithms are part of the same efficient frontier. The results concerning the spacing metric and diversity metric are relatively insensitive to the mutation rate. The S-metric shows a slightly better result with a mutation rate of 0.2.

The results of the C-metric and D-metric are presented in Table 5.4. The results indicate that there is no algorithm that completely covers the results of another algorithm, hence a single best approach cannot be indicated. It also shows that the algorithms with a population size of 50 are in general more covered and that the SPEA2+ approach shows on average a larger coverage of other algorithms.

Table 5.4 Overview results C-metric and D-metric

C-metric, *CTS*									
Approach				*Population size*			*Mutation Rate*		
	NSGAII	*SPEA2*	*SPEA2+*		*100*	*50*		*0.2*	*0.05*
NSGAII		0.12	0.09	*100*		0.26	*0.2*		0.15
SPEA2	0.20		0.11	*50*	0.07		*0.05*	0.17	
SPEA2+	0.23	0.18							
C-metric, *NONDOM*									
Approach				*Population size*			*Mutation Rate*		
	NSGAII	*SPEA2*	*SPEA2+*		*100*	*50*		*0.2*	*0.05*
NSGAII		0.80	0.77	*100*		0.89	*0.2*		0.84
SPEA2	0.89		0.83	*50*	0.82		*0.05*	0.87	
SPEA2+	0.92	0.91							
D-metric, *$CDTS_{rel}$*									
Approach				*Population size*			*Mutation Rate*		
	NSGAII	*SPEA2*	*SPEA2+*		*100*	*50*		*0.2*	*0.05*
NSGAII		2.20%	1.54%	*100*		1.71%	*0.2*		1.75%
SPEA2	1.14%		1.07%	*50*	1.39%		*0.05*	1.29%	
SPEA2+	1.36%	1.95%							

Table 5.4 also shows the results of the D-metric, in this case the $CDTS_{rel}$ measure. This measure shows that although the SPEA2+ approach has a higher coverage, the volumes associated with this is not necessarily larger. The comparison between SPEA2+ and NSGAII shows that the C-metric is higher for the SPEA2+, but the D-metric is larger for NSGAII. This is also the situation when SPEA2 and NSGAII are compared. These results are consistent with the better performance of NSGAII on the S-metric. The results on the C-metric are relatively insensitive for the mutation rate. The D-metric shows that the average difference in space coverage is larger for the mutation rate of 0.2 versus 0.05.

5.2.3 Conclusions

In bi-level multi-objective optimization studies, solution approaches using GAs have been proven successful. Three algorithms were implemented and tested in a case study. The analysis of convergence shows that the largest improvements are found after 5,000 solutions.

However, there are still improvements possible when increasing the number of generations. The results indicate that the SPEA2 and mainly the SPEA2+ approach are able to obtain a more diverse solution set in the objective space as well as in the solution space than the NSGAII approach. However, the NSGAII approach is able to obtain a slightly larger space coverage. The SPEA2+ approach is also able to cover more of the sets attained by the NSGAII and SPEA2 approach, but the NSGAII approach obtains a larger space coverage difference. On average, the SPEA2+ outperforms the SPEA2 in this optimization problem on all used measures. Comparing NSGAII and SPEA2+, there is no clear evidence of one approach outperforming the other. Both approaches can therefore be used to solve the MO NDP of this research. The size of the population influences the performance on the measures. A larger population results on average in a larger space coverage, while a smaller population size results in higher performance on spacing and diversity. Most performance measures are relatively insensitive for the mutation rate, only the space coverage related measures, i.e. S-metric and D-metric show slightly better results for the mutation rate of 0.2 versus 0.05.

5.3 Acceleration using response surface methods

5.3.1 Approximation methods

Heuristics used to solve the upper level, like the presented algorithms in Section 5.2, usually require a large number of function evaluations (i.e. evaluation of objective functions of possible solutions). Every evaluation requires solving the dynamic UE problem by the DTA model, which is computationally expensive, especially in large scale real world applications. To relax these time-consuming optimization procedures, it may be of interest using approximation methods to reduce the time needed to evaluate solutions or the number of solutions being evaluated exact. Approximation methods estimate the outcome of a function evaluation on the basis of previously observed objective functions of exact evaluated (neighboring) individuals.

Different approximation methods are available, such as functional approximation using kriging, radial basis functions (RBF), RSM and evolutionary approximation using clusters and fitness inheritance (Santana-Quintero et al., 2010; Shi and Rasheed, 2010; Fikse, 2010). Fitness inheritance and clusters are evolutionary approximation methods, which are specific for EAs. The outcome of the function evaluations of the different assessed solutions and mutual comparison determine the fitness of the solutions within an MOGA. The method of fitness inheritance assigns fitness to a solution by the average (or weighted average) of the fitnesses of its parents. Clearly, also exact fitness function values are required to obtain enough information. Ducheyne et al. (2008) concluded that fitness inheritance methods can be used for convex and continuous problems, which is not the case in this MO NDP. The second evolutionary approximation method is a class of methods using clustering techniques. There is no generic approach that uses clustering. In the adaptive fuzzy fitness granulation (AFFG) it is for example used to assign fitness to a solution based on the fitness of solutions that are assigned to the same cluster in solution space (Davarynejad et al. (2010). The kriging, RBF and RSM methods are functional approximation methods in which a new expression is constructed for the objective functions based on previous data obtained from exact evaluations. These models are also known as meta-models or surrogates. Based on research by Fikse (2010) in which kriging, RBF and RSM are compared for MO NDP, the RSM was selected as approximation method for this research. This decision was based on its performance, simplicity, computational cost and it does not require any tuning of parameters. This was also concluded in other research (Shi and Rasheed, 2010).

Two of the rare studies in which function approximation is used within traffic and transport optimization problems, are research by Osorio and Bierlaire (2011) and Chow (2010). Osorio and Bierlaire used the trust region optimization method to optimize fixed-time signal control problem. Trust region optimization uses RSM methods and is applicable for single objective optimizations. Chow developed and applied the multi-objective radial basis function algorithm for solving a single objective and bi-objective CNDP.

5.3.2 Response surface methods

The RSM is introduced by Box and Wilson (1951) and was originally intended as a guideline to design experiments. In this case a regression model is fitted, using a pure quadratic polynomial (single and quadratic terms), which is also recommended in other studies (Osorio and Bierlaire, 2011; Fikse, 2010; Shi and Rasheed, 2010):

$$\tilde{z}_i = \chi_0 + \sum_{t=1}^{T}\sum_{b=1}^{B} \chi_{(t-1)*T+b} s_b^t + \sum_{t=1}^{T}\sum_{b=1}^{B} \chi_{TB+(t-1)*T+b} s_b^{t\,2} \quad (5.8)$$

By fitting a regression model, a least square problem is solved using the exact evaluated solutions as input and results in the estimates for the parameters χ_j. To be able to solve the least square problem (finding a unique solution) the number of exact evaluated solutions that form the input should be at least equal to the number of parameters χ_j to estimate. However, to avoid over fitting, the number of exact evaluated solutions should be larger. In addition, because the MO NDP is not specifically interested in one part of the solution space, the model is used for global approximation. To avoid fast convergence to local optima, diversity of exact evaluated solutions, which are used for fitting the regression model is relevant. Using this type of model is easy to understand and can be estimated fast, even with a large number of exact evaluated solutions.

5.3.3 Algorithms using RSM

The surrogate model estimated by RSM methods can be used in different ways in combination with MOGAs. Main differences depend on the level of confidence in the estimated surrogate model. The surrogate model can be used as a pre-evaluation to determine the solutions that should be evaluated exact, as fitness evaluation in which the estimates are used as exact values or as design of experiments in which the surrogate model is used to define solutions that should be exactly evaluated. These possible options are part of the algorithms compared. Because the comparison of the MOGAs in Section 5.2 showed that the SPEA2+ algorithm performs well for the dynamic MO NDP and shows more diversity in solution and objective space than the other tested algorithms, which is relevant for the estimation of the surrogate model, this algorithm is used as a starting point.

Within the first approach (SPEA2+ pre evaluation FA) the surrogate model is used as a pre-evaluation within the SPEA2+ algorithm to determine which ‘children’ are interesting to evaluate exactly. In this case a solution is interesting when it, according to the approximation, is a non-dominated solution. In addition, the children that are situated in less dense areas are also interesting and included to evaluate exactly, because these solutions can improve the surrogate model and because the error of the approximation of these solutions is relatively high. If the algorithm tends to converge, the pre-evaluation is neglected, which means that the algorithm becomes a regular SPEA2+ algorithm. The advantage of this approach is that it still uses the full characteristics of the original heuristic and is not fully dependent on the quality of the surrogate model. However, it is possible that only a limited number of solutions are not exactly evaluated and therefore the acceleration is limited. Within the second approach (FA optimized SPEA2+), the surrogate model itself is optimized using a SPEA2+ algorithm. The resulting solutions are exactly evaluated to determine the Pareto optimal set and used to update the approximation set. The advantage of this algorithm is that the surrogate model is fully used, which in theory can result in the largest acceleration possible. However, this also means that the quality of the surrogate model is determinative for the Pareto optimal set found and can result in erroneously not considering solutions in certain parts of the solution space. Within the third approach (FA seeded SPEA2+) the algorithm of the second approach is only used in the first generations, whereafter the algorithm continues as a regular SPEA2+ algorithm. In this algorithm the surrogate model is used to obtain a seeded starting population. The advantage is that it combines the second approach with the original heuristic assuming that the largest acceleration is found in the first steps and therefore avoids fast convergence to sub-optimal solutions. However, this also means that only in the first steps acceleration is possible.

All algorithms use a Latin Hypercube Sample (LHS) optimized for correlation as a starting population. This LHS is used as input (approximation set) for estimating the surrogate model. In all algorithms this approximation set is updated based on new solutions exactly evaluated. Within the SPEA2+ pre evaluation FA and seeded SPEA2+ new solutions are added if these provide information for low dense areas in the solution space. Within the FA optimized SPEA2+ the approximation set consists of all exact evaluated solutions. This approximation set is combined with the Pareto optimal set known thus far, forming the training set to estimate the surrogate model.

SPEA2+ pre evaluation FA

Step 1: *Initialization*: Set population size W_p, which is equal to the archive size W_u, the maximum number of generations *H*, and generate an initial population OU_0. Set $h = 0$, $DU_0 = \varnothing$ and $Q_0 = \varnothing$.

Step 2: *Fitness assignment*: Combine archive OU_h, DU_h and children Q_h, forming $Y_h = OU_h \bigcup DU_h \bigcup Q_h$, and calculate fitness values of solutions by strength values and density information.

Step 3: *Environmental selection*: Copy al non-dominated solutions in Y_h to new archives OU_{h+1} and DU_{h+1}. If size of OU_{h+1} and DU_{h+1} exceeds W_u, then reduce OU_{h+1} by truncation using distances in the objective space and DU_{h+1} by truncation using distances in the solution space, otherwise if less than W_u, then fill OU_{h+1} and DU_{h+1} with best solutions out of Y_h based on their fitnesses.

Step 4: *Update training set:* If $h = 0$ set approximation set $\Psi_{h+1} = OU_0$, otherwise update approximation set Ψ_{h+1} with solutions of offspring Q_h that are situated in less dense areas based on distance k-th nearest neighbor in solution space. Combine approximation set Ψ_{h+1} and DU_{h+1} if truncation procedure is used, otherwise combine Ψ_{h+1} and OU_{h+1} forming the training set $\Phi_{h+1} = \Psi_{h+1} \bigcup DU_{h+1}$, or $\Phi_{h+1} = \Psi_{h+1} \bigcup OU_{h+1}$.

Step 5: *Function approximation:* Estimate surrogate objective functions $\tilde{z}_i = f(S)$ based on training set Φ_{h+1}

Step 6: *Termination*: If $h \geq H$ or another stopping criteria is satisfied, then set X^* to the set of solutions part of DU_{h+1} with fitness value smaller than 1 (non-dominated solutions) and determine the size of non-dominated solutions *W*, note that $W \leq W_u$.

Step 7: *Mating selection*: If truncation procedure is used, select DU_{h+1} as mating pool of parents P_{h+1}, otherwise if not, select OU_{h+1} as mating pool of parents P_{h+1}.

Step 8: *Variation*: Apply neighborhood crossover and mutation operators to the mating pool P_{h+1} to create offspring Q_{h+1}.

Step 9: *Pre-evaluation:* Skip pre-evaluation if results tend to converge (based on C-metric), otherwise evaluate offspring Q_{h+1} using surrogate objective functions and update Q_{h+1} by removing children that will not be part of the Pareto optimal set. Add children to Q_{h+1} that are situated in less dense areas based on k-th nearest neighbor in solution space. Set $h = h+1$ and go to step 2.

FA optimized SPEA2+

Step 1: *Initialization*: Set population size W_p, which is equal to the archive size W_u, the maximum number of generations *H*, and generate an initial population OU_0. Set $h = 0$, $DU_0 = \varnothing$ and $Q_0 = \varnothing$.

Step 2: *Fitness assignment*: Combine archive OU_h, DU_h and children Q_h, forming $Y_h = OU_h \bigcup DU_h \bigcup Q_h$, and calculate fitness values of solutions by strength values and density information.

Step 3: *Environmental selection*: Copy al non-dominated solutions in Y_h to new archives OU_{h+1} and DU_{h+1}. If size of OU_{h+1} and DU_{h+1} exceeds W_u, then reduce OU_{h+1} by truncation using distances in the objective space and DU_{h+1} by truncation using distances in the solution space, otherwise if less than W_u, then fill OU_{h+1} and DU_{h+1} with best solutions out of Y_h based on their fitnesses.

Step 4: *Update training set:* If $h = 0$ set training set $\Phi_{h+1} = OU_0$, otherwise combine training set Ψ_h and solutions of offspring Q_h to update training set $\Phi_{h+1} = \Phi_h \bigcup Q_h$.

Step 5: *Function approximation:* Estimate surrogate objective functions $\tilde{z}_i = f(S)$ based on training set Φ_{h+1}

Step 6: *Termination*: If $h \geq H$ or another stopping criteria is satisfied, then set X^* to the set of solutions part of DU_{h+1} with fitness value smaller than 1 (non-dominated solutions) and determine the size of non-dominated solutions *W*, note that $W \leq W_u$.

Step 7: *Optimize surrogate model:* Optimize surrogate objective functions using regular SPEA2+ algorithm. Set resulting Pareto optimal set as offspring Q_{h+1}. Set $h = h+1$ and go to step 2.

FA seeded SPEA2+

Step 1: *Initialization*: Set population size W_p, which is equal to the archive size W_u, the maximum number of generations *H*, and create seeded initial population using FA optimized SPEA2+ algorithm for 3 generations. Set resulting Pareto optimal set as initial population OU_0. Set $h = 0$, $DU_0 = \varnothing$ and $Q_0 = \varnothing$.

Step 2: *Fitness assignment*: Combine archive OU_h, DU_h and children Q_h, forming $Y_h = OU_h \bigcup DU_h \bigcup Q_h$, and calculate fitness values of solutions by strength values and density information.

Step 3: *Environmental selection*: Copy al non-dominated solutions in Y_h to new archives OU_{h+1} and DU_{h+1}. If size of OU_{h+1} and DU_{h+1} exceeds W_u, then reduce OU_{h+1} by truncation using distances in the objective space and DU_{h+1} by truncation using distances in the solution space, otherwise if less than W_u, then fill OU_{h+1} and DU_{h+1} with best solutions out of Y_h based on their fitnesses.

Step 4: *Termination*: If $h \geq H$ or another stopping criteria is satisfied, then set X^* to the set of solutions part of DU_{h+1} with fitness value smaller than 1 (non-dominated solutions) and determine the size of non-dominated solutions *W*, note that $W \leq W_u$.

Step 5: *Mating selection*: If truncation procedure is used, select DU_{h+1} as mating pool of parents P_{h+1}, otherwise if not, select OU_{h+1} as mating pool of parents P_{h+1}.

Step 6: *Variation*: Apply neighborhood crossover and mutation operators to the mating pool P_{h+1} to create offspring Q_{h+1}. Set $h = h+1$ and go to step 2.

5.3.4 Comparison algorithms

Set up comparison algorithms

To compare the algorithms, case 1, which is described in Chapter 4, and a selection of the objectives, namely efficiency, climate and noise, is used. Results of the algorithms are compared with the results of regular SPEA2+ (base case). Because the performance of the algorithms is of interest when the computation time is restricted, the budget of solutions that can be considered is limited. The analysis is therefore focusing on how well the algorithms perform given the same available computation time. In the comparison of the approaches, the total number of solutions evaluated after the initialization is a fixed number of 5,000 solutions. For all algorithms the same genetic operators are used, namely uniform crossover and mutation. The initial mutation probability ρ_{mut}^{init} was 0.2, which decreased every generation with 5% for the first 10 generations. All approaches are repeated 8 times and the archive size was set to be equal to the population size of 100 solutions.

Results comparison

Figure 5.3 shows the Pareto optimal solutions of one random chosen application for each algorithm. These results show that the algorithms find solutions in similar parts of the objective space. Analyzing the found minima (i.e. absolute minima and average minima of repetitions) of the three objective functions concerning efficiency, climate and noise shows that the differences compared to the regular SPEA2+ algorithm are less than 1 percent. The differences in found maxima for climate and noise are also less than 1 percent. For efficiency the differences for SPEA2+ pre evaluation FA is less than 1 percent, for FA seeded SPEA2+ less than 1.5 percent and for FA optimized SPEA2+ less than 1.6 percent. Therefore, the use of approximation methods within the proposed algorithms does not result in missing relevant parts of the Pareto optimal set. To compare the algorithms in more detail the different performance measures are analyzed.

The average performance of the algorithms after the algorithms have terminated (after a fixed available computation time), is presented in Table 5.5. These results show that the differences between the algorithms are small. The SPEA2+ pre evaluation FA performs slightly better than the SPEA2+ algorithm and the other algorithms slightly less. The similar performance also means that the use of approximation methods does not result in bad performance, because of wrong decisions based on the surrogate model.

Table 5.5 Overview of performance algorithms

	S-metric	**C-metric***		**Spacing (obj)**	**Spacing (sol)**
		X',X"	**X",X'**		
SPEA2+	2.03E+11	0.00	0.00	0.37	0.20
SPEA2+ pre evaluation FA	2.03E+11	0.19	0.10	0.36	0.20
FA seeded SPEA2+	2.00E+11	0.14	0.17	0.44	0.22
FA optimized SPEA2+	2.01E+11	0.14	0.18	0.55	0.16

* X'' is set of solutions SPEA2+

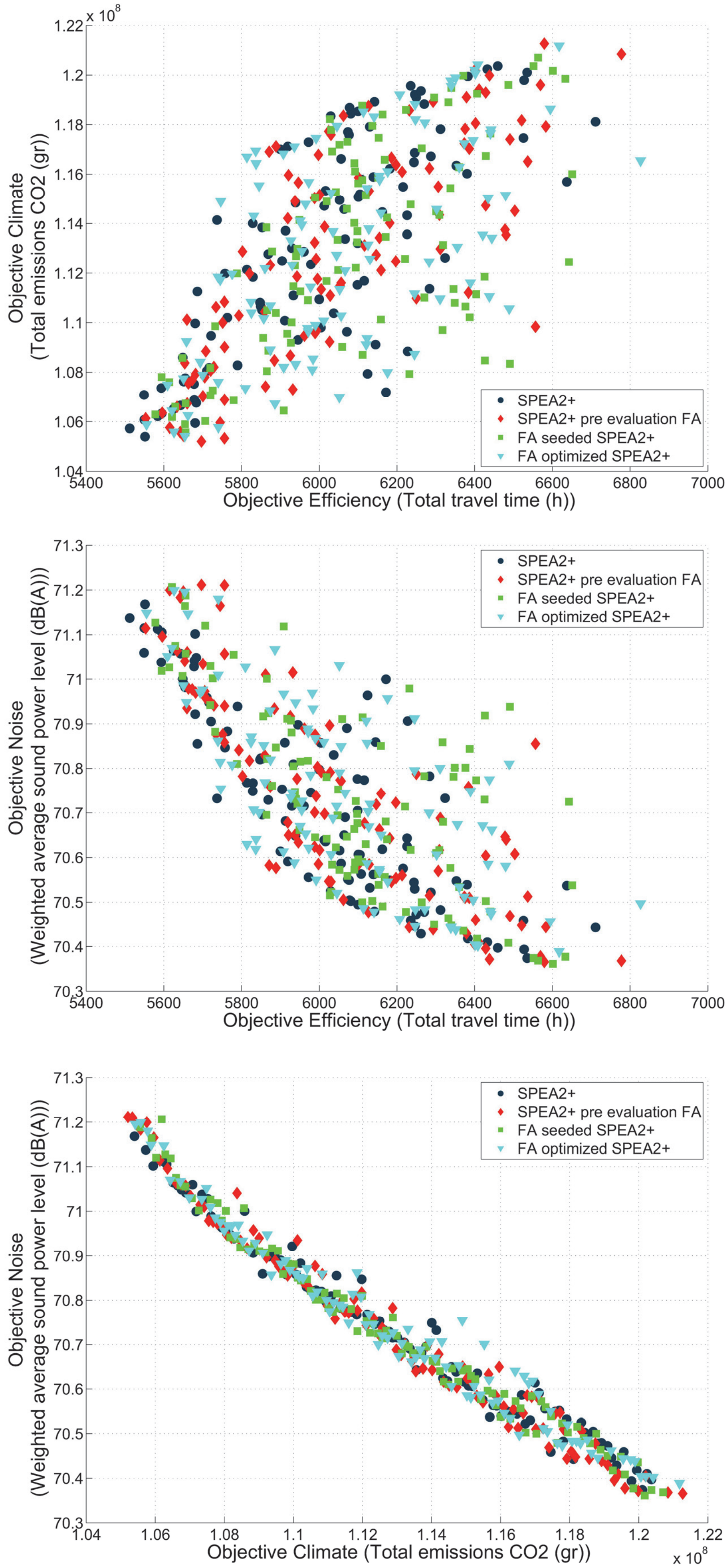

Figure 5.3 Pareto optimal solutions

One of the reasons the algorithms perform similar, is because the results are converging, meaning that all algorithms, also the regular SPEA2+ algorithm, do not find new solutions resulting in major improvements in the last generations. The time given in this test case is enough for all algorithms to find a reasonably good performing set of solutions. Therefore, it is also of interest how the performance of the algorithms develops over the number of solutions exactly evaluated.

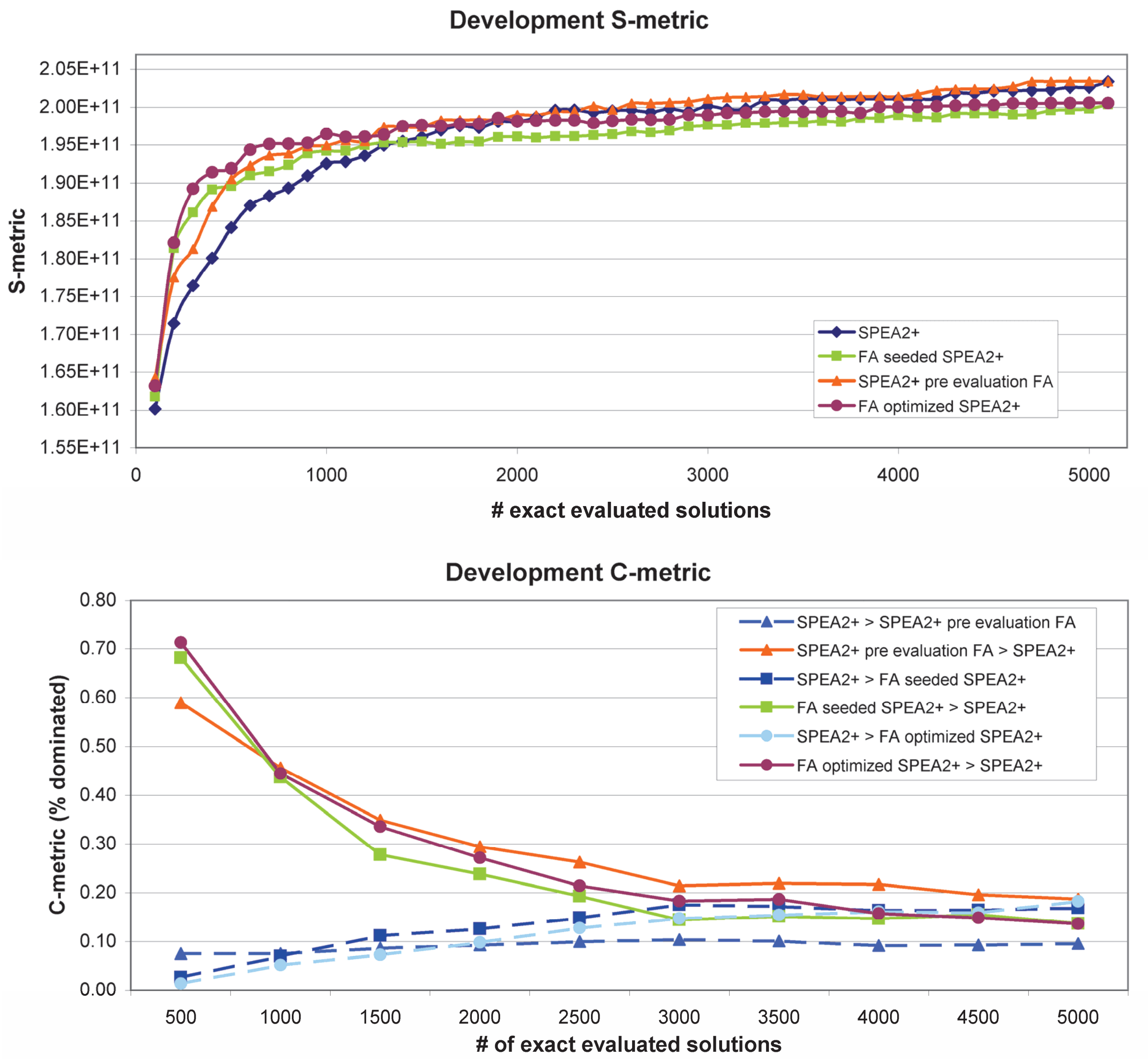

Figure 5.4 Development C-metric and S-metric

In Figure 5.4 the development of the S-metric and C-metric is shown. In these figures the performance is presented dependent on the exact evaluated solutions. For the C-metric the regular SPEA2+ is used as the reference case (e.g. after 500 exact evaluated solutions the SPEA2+ pre evaluation FA dominates on average 59% of the solutions of regular SPEA2+ and regular SPEA2+ dominates on average 8% of the solutions of SPEA2+ pre evaluation FA. The development of both performance measures shows that all three algorithms using function approximation show better results at least till 1,500 solutions are exactly evaluated. This means that with less exact evaluated solutions the algorithms using RSM methods already found good solutions. However, the algorithms are not capable in maintaining their head start. This can be explained, because the quality of the surrogate model determines the effectiveness of using such models within the algorithms. The surrogate model does push the search in good directions at the start, but after a certain number of generations the contribution of the surrogate model in guiding the search is diminishing. In addition, after some generations the quality of this surrogate model does not improve anymore, although more solutions are exactly evaluated and used as training set. The results show that when using these RSM methods, the optimization tends to converge faster, possibly to a local optimum or a less performing set of solutions. The extent in which this occurs, depends on the level of confidence in the estimated surrogate model, which varies in the algorithms compared. Therefore, these methods are mainly of interest if a limited number exact evaluations can be done or can be used as a pre phase in a hybrid approach. To avoid premature convergence two algorithms proceed with regular SPEA2+ in which the FA seeded SPEA2+ has difficulties to find further improvements, whereas the SPEA2+ pre evaluation FA performs at least similar in these generations as the regular SPEA2+ algorithm. This results in a slightly better performance of the SPEA2+ pre evaluation FA than the regular SPEA2+ algorithm after the final generation.

5.3.5 Conclusions

To accelerate the solution approach, approximation methods can be used in various ways as part of an MOGA. Three different algorithms were tested. Comparison of the algorithms shows that the use of RSM methods does find solutions in similar parts of the objective space as regular SPEA2+ and therefore does not result in missing relevant parts of the Pareto optimal set. The average performance of the algorithms, given the chosen fixed computation time budget, is similar in which the SPEA2+ pre evaluation FA performs slightly better than regular SPEA2+. The development of the performance measures shows that the algorithms using RSM methods accelerate the search at the start considerably. With less exact evaluated solutions already good solutions are found. However, the algorithms using these RSM methods tend to converge faster, possibly to a local optimum and therefore loose their head start, because these algorithms depend largely on the quality of the surrogate model. Therefore, these methods are of interest for the MO NDP of this research, because for larger networks a limited number exact evaluations can be done and a reasonable performing set of solutions is satisfactory. Although, the algorithms using RSM methods all used SPEA2+ as a base case, the methods can also be used for other EAs as well, with possibly similar advantages and deficiencies depending of the quality of the solutions proposed by these algorithms.

5.4 Optimization of approach

In addition to the use of approximation techniques, also other techniques can be used to accelerate the search. One important one, which is possible as a result of the characteristics of the presented GA, is using distributed computing. All children that are produced in a generation can be assessed parallel, because there is no dependency between them. Other possible accelerations are related to compromising the original optimization problem. Possible options are using one or multiple reference solutions to accelerate solving the lower level or decreasing solution space by using expert judgment. Using reference solutions assumes that the differences in route choice effects between a solution being evaluated and an appropriate reference solution is relatively small. In this approach the route flows of the dynamic UE of the reference solution are used as the initial start for the evaluation of a new solution. In the case of multiple reference solutions, a diverse set of reference solutions can be selected using LHS or an orthogonal design. LHS is also used in the presented solution approaches using RSM assisted MOGA. Choosing an appropriate reference model can be done using cluster analysis in solution space to determine the best fitting reference model for a new solution to evaluate.

The second option, using expert judgment, means incorporating knowledge into the design for example by minimizing the possible settings for a certain DTM measure or by combining measures (i.e. if a certain traffic signal is used to meter traffic it influences the way a downstream traffic signal can be used to influence traffic). Using this approach assumes that non-interesting solutions can be excluded beforehand. In Wismans et al. (2010) it is shown for one test case that if it is possible to restrict the solution space intelligently for the single objective case, this will not yield sub-optimal solutions. Within this research a static version $\underline{SO\ NDP}_i$ of the original single objective (SO) NDP problem $SO\ NDP_i$ is introduced in the sense that the application of available DTM measures is fixed for the total time period (i.e. $\underline{s}_b^t = \underline{s}_b \forall t$).

The original SO NDP is defined by:
$SO\ NDP_i : z_i$, subject to $\left(q(S), v(S), k(S)\right) \in \Gamma^{DTA}\left(G\left(N, A\left(C(S)\right)\right), D\right)$, and $F = \left\{S \mid s_b^t \in \{1,...,M_b\}, \forall b,t\right\}$, and results in the optimal solution S_i^*,
The static version by:
$\underline{SO\ NDP}_i : z_i$, subject to $\left(q(S), v(S), k(S)\right) \in \Gamma^{DTA}\left(G\left(N, A\left(C(S)\right)\right), D\right)$, and $\underline{F} = \left\{S \mid s_b \in \{1,...,M_b\}, \forall b\right\}$, and results in the optimal solution $\underline{S}_i^*$.

Assuming that the optimal solution of the static version will also be a good solution for the original SO NDP, this information can be used to determine a seeded starting population and to reduce solution space. Both optimization problems were solved using a GA and two approaches were tested in which this static version was used as a pre-optimization. In the first approach the optimal solution $\underline{S}_i^*$ was used to determine the initial population of the optimization of the original SO NDP, in which $U_0 = \left\{S \mid \delta\left(s_b^t, \underline{s}_b^*\right) < \varepsilon_1, \forall b,t\right\}$. In the second approach this was also used and the feasible space was reduced by $\tilde{F} = \left\{S \mid d\left(s_b^t, \underline{s}_b^*\right) < \varepsilon_2, \forall b,t\right\}$ and $\varepsilon_2 > \varepsilon_1$. These two approaches were compared with solving the original SO NDP directly using GA for all single objectives. Although, both approaches did not yield sub-optimal solutions, this research also showed that using a pre-optimization to restrict solution space and determine a seeded initial population did not enhance the optimization process. The main reason for this was related to the time needed to carry out the pre-optimization. However, if the time needed to restrict solution space or to determine a seeded initial population can be reduced (e.g. by using expert judgment) the optimization procedure can be accelerated further.

5.5 Concluding remarks

In this chapter the challenges of solving the upper level of the bi-level optimization problem are addressed. Because the MO NDP is non-convex, non-differentiable and NP-hard, a heuristic is needed to solve this problem. Other approaches are also possible, as mentioned in Chapter 2, but often means simplifying the problem (e.g. linearizing the problem) of which the realism and performance can be questionable. In addition, no research was found in which the dynamic NDP was reformulated for multi-destination networks. Heuristics are methods that intelligently search optimal solutions in solution space and are subject to the no free lunch theorem. Testing of algorithms is therefore necessary and carried out in this research. Two algorithms NSGAII and SPEA2+ turned out to perform well. Next to the tested algorithms, which are chosen because of their performance according the literature on other optimization problems and some also on other MO NDP problems, there is an increase in possible heuristics, mainly EA (e.g. ant colony), that are possibly of interest. However, all possible heuristics still need a large number of function evaluations to optimize and can be computationally expensive, especially when solving the lower level already needs large computation times. Acceleration of the search is therefore of importance. In this research various algorithms are tested using RSM. Using a surrogate model, which can be seen as incorporating knowledge into the algorithm, shows that it is possible to accelerate the search in the first generations and therefore useful. The quality of the surrogate model, which also depends on the complexity of objective space, determines to what extent acceleration is possible. Point of attention, important when using heuristics and connected with the no free lunch theorem, is setting the parameters of the algorithms, especially because the optimal settings depend on the optimization problem at hand.

There are additional options to accelerate the search like distributed computing, which does not influence the eventual outcome, and reducing calculation time solving the lower level like marginal computing (Corthout et al., 2011), which does influence the quality of the outcome. Expert judgment is also a possible option to accelerate the search, e.g. to reduce solution space. Although this is certainly an option for SO NDP, it is questionable if this is also possible for the MO NDP, which is far more complex. Pareto optimal solutions can e.g. be part of almost all areas in solution space. However, optimization of real cases can provide knowledge to improve or accelerate the optimization procedure.

Based on the results presented in this chapter, some of the approaches are used in the test cases of chapter 7. However, solving the MO NDP results in a Pareto optimal set of solutions. This set provides valuable information for the decision making process, e.g. trade offs between objectives, which would not have been available if the compensation principle would have been chosen in advance (i.e. solving a single objective NDP with a weighted sum of all objectives). In the end one solution has to be chosen for implementation, which represents the best compromise solution. The Pareto optimal set can be used to learn about the problem and solutions possible to assist the decision maker, which is addressed in chapter 6.

Chapter 6

Decision support

Als je goede informatie hebt, is de kans dat je goede beslissingen maakt vrij groot
If you have good information, there is a good chance you are making the right decision
Johan Cruijff

In Chapter 5 solution approaches are presented that can solve the MO NDP. The multi-objective optimization has the advantage of considering all possible strategies, resulting in the Pareto optimal set, instead of evaluating a few predefined strategies. However, in both cases decisions are needed concerning the compensation principle, to be able to choose a certain strategy to implement (i.e. the best compromise solution). The Pareto optimal set contains valuable information to support this decision making process, which allows the decision makers to learn about the problems and solutions before choosing a certain strategy. It may be of importance to present decision makers the main choices. Pruning methods may be useful to circumvent the possible difficulties in analyzing and comprehending the large Pareto optimal set in the decision making process. The eventual choice of the best compromise solution is a public policy decision that determines the compensation principle. Often cost-benefit analysis is used as the appraisal method in traffic and transport. However, the question arises if this is the most suitable approach for the deployment of DTM measures as well. This chapter discusses the valuable information like trade-offs, which is contained by the Pareto optimal set and pruning methods. Additionally, the consequences of using cost-benefit analysis is presented and discussed, as well as other methods using multi-criteria decision making methods to rank the solutions. These methods can be used as a basis of an interactive decision support tool to choose the best compromise solutions.

This chapter first describes the step of decision support concerning choosing the best compromise solution. Then the information contained by the Pareto optimal set is described in general. Methods to prune the Pareto optimal set are discussed and applied to illustrate the advantages and disadvantages. The often used cost-benefit analysis is applied in a case study to show the consequences and other methods to rank solutions are discussed and applied as well.

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Wismans, L. J. J., E.C. van Berkum & M. C. J. Bliemer (2012). Optimization of externalities as objectives for dynamic traffic management, choices necessary. *Submitted for EJTIR (under review).*

6.1 Introduction

When multiple objectives are considered, decisions are needed to be able to choose the solution to implement (i.e. the best compromise solution). These decisions are mainly related to the compensation principle that should be used to weigh the various objectives. Within the field of traffic and transportation, this choice is a public policy decision. In this case this means that decision makers for example need to decide how much increase in emissions is accepted in exchange for a decrease in total travel times. Such decisions are not only needed when the Pareto optimal set is known after solving the MO NDP, but also when a limited number of predefined solutions are considered. Setting these weighting factors is difficult to determine in advance, especially because it is difficult to foresee what the consequences are. Steenbrink (1974) already concluded that it is impossible to formulate a single objective function in which all relevant factors are included completely and consistently between the objectives. When it would be possible to set the weights in advance, it also becomes possible to turn the MO NDP into a SO NDP by using a weighted sum of the objectives. However, as indicated in Chapter 1, knowledge is lacking on how the objectives relate on network level and what the consequences are of choosing a certain compensation principle or implementing a certain strategy. Solving the MO NDP results in the Pareto optimal set and has the advantage that the compensation principle is not needed beforehand. This Pareto optimal set provides the possibility to learn about the problem at hand and solutions possible, before deciding how to weigh the various objectives. The knowledge contained in the Pareto optimal set is about the extent in which the individual objectives can be influenced with the decision variables (i.e. what is the lower and upper bound), about the trade-offs and how the various objectives are related. Based on this set it is possible to determine the consequences when a certain compensation principle is used and how sensitive the outcome is for the used principle. In addition, this way it is also possible to use other procedures to choose the best compromise solution to implement or select solutions for closer investigation. The analysis of these aspects can be used within an interactive decision support tool, providing decision makers the opportunity to make a more deliberate choice.

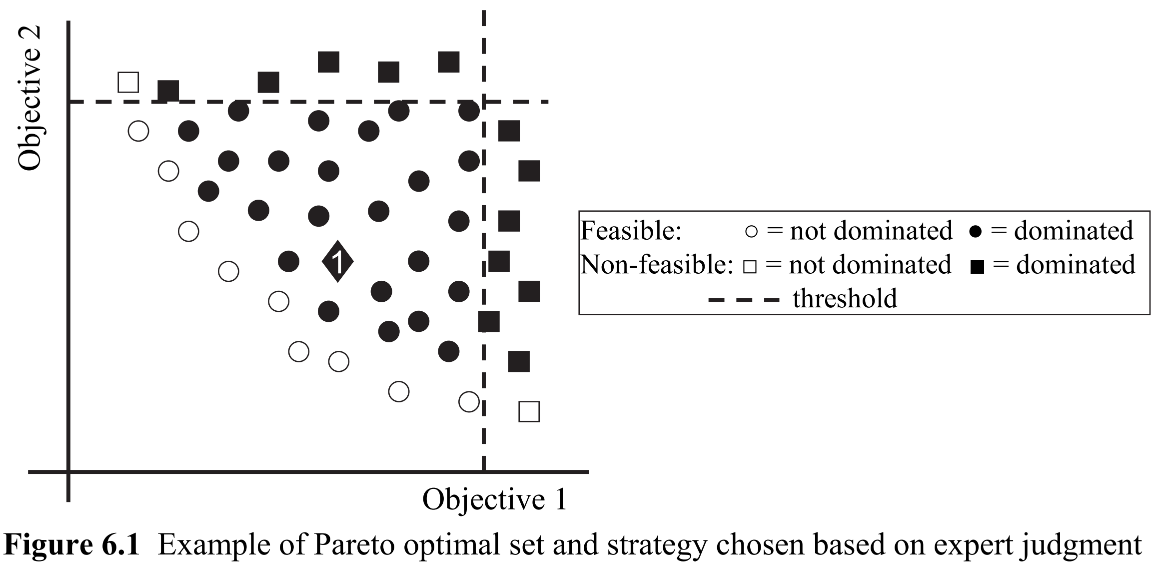

Figure 6.1 Example of Pareto optimal set and strategy chosen based on expert judgment

State-of-practice is to formulate a limited number of alternative strategies or even a single strategy based on expert judgment, not knowing whether these are optimal or relevant strategies are missing. Within the STM process for example, introduced in Chapter 1 and often used in the Netherlands to determine traffic management strategies for regions in which multiple road management authorities are involved, pre-determined threshold values (e.g. minimum average speed on a corridor) are used to evaluate the effectiveness of a strategy. However, when a strategy complies with these thresholds, it is still uncertain if this strategy is optimal and like setting weighting factors, setting these thresholds beforehand, is not trivial. See for example Figure 6.1 in which all solutions that comply with the hypothetical formulated thresholds are marked feasible. Assuming that within the STM process solution 1 (diamond solution) is formulated, means that this solution complies with the formulated thresholds. However, this solution is not Pareto optimal, because solutions are available that can improve both objectives. The Pareto optimal set is a result of optimizing all objectives considering all possible strategies, which means the best compromise solution can be chosen by the decision makers using this set.

However, the Pareto optimal set of solutions can become large, especially if the objectives are mainly opposed. As a consequence the Pareto optimal set may become difficult to analyze and to comprehend. In this case pruning this set can be used to assist the decision maker, which is also argued in Chaudhari et al. (2010). Pruning means reducing the Pareto optimal set retaining its main characteristics. By pruning the Pareto optimal set, it is possible to provide a comprehensive analysis of the main choices for the decision makers, which can also be used to choose an appropriate compensation principle. The pruned Pareto optimal set should therefore contain the solutions that show significance differences, the extremal solutions and an equal spread along the efficient frontier. A hypothetical outcome of such pruning is presented in Figure 6.2. The acceptable size of the pruned Pareto optimal set is arbitrary. Given the decision making processes in the field of traffic and transportation in practice, the size should be as small as possible, still offering decision makers the possibility to choose. There are various pruning methods possible, which will be further addressed in this chapter.

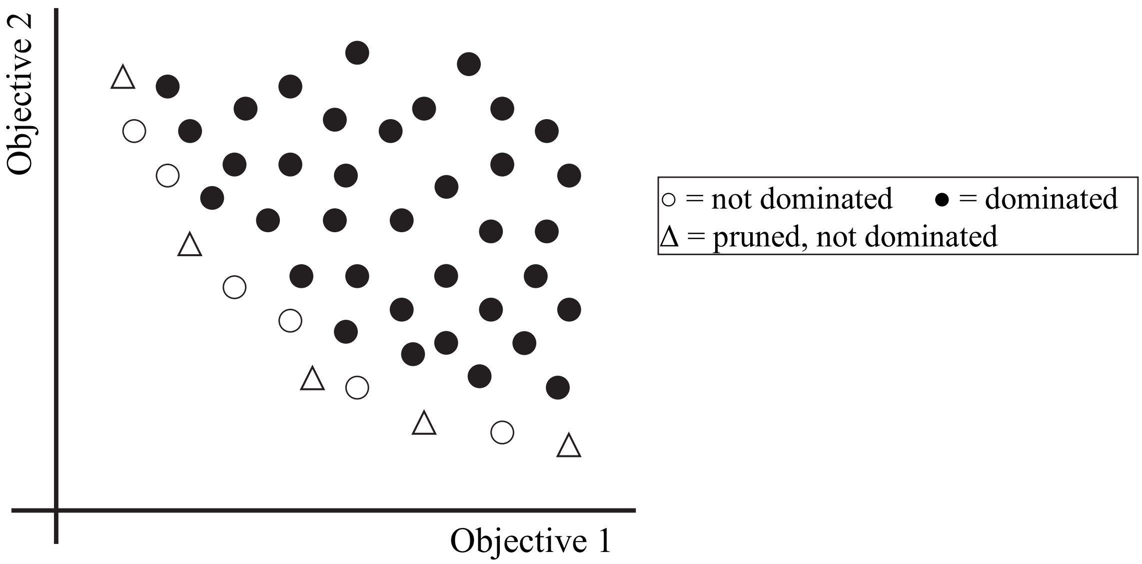

Figure 6.2 Example of pruned Pareto optimal set

Applying a certain compensation principle to rank solutions is closely related to multi-criteria decision making (MCDM) methods. Using a weighted sum of the objectives is similar to the probably most widely known and used weighted sum method. The MCDM methods deal with the evaluation of a set of alternatives using a set of decision criteria to choose the best or select a few good compromise solutions for closer investigation. These methods are already important instruments for decision making processes in which a predefined set of alternatives are compared. Cost-benefit analysis (CBA) in which the effects are monetized, which means monetary value are used as weighting factors, is an often used appraisal method within the field of traffic and transportation. However, the consequences of this method are rarely addressed and the availability of the Pareto optimal set makes it possible to investigate these consequences. CBA is possibly not the best suitable approach for the deployment of DTM measures and therefore also other methods may be of interest within a decision support tool. Because the method applied, may influence the eventual decisions made, it is important to choose methods that corresponds best with the underlying decision process and are in accordance with the qualities of the data related to the presented MO NDP.

The current process of determining the deployment of DTM measures is heterogeneous and differs per municipality, region and country. In general it is "problem-driven" and the focus also depends on the political agenda. The incorporation of externalities as objectives in the deployment of DTM is relatively new and road management authorities are searching for ways to cope with these objectives. This is also one of the reasons for this research, to provide knowledge on how the objectives interact and what strategies can be deployed. Within the STM process, compensation principles are not explicitly formulated when externalities are considered and when externalities are considered these are in most cases implicitly taken into account as constraints (e.g. flow at road x may not exceed a certain thresholds, because of livability problems). This means that traffic engineers themselves have to decide on tactical level how to cope with the various objectives. As a result, the extent in which externalities are taken into account in the deployment of DTM measures often depends of the formulated general policy objectives and expert judgment of the involved traffic engineers. However, these decisions of traffic engineers still need to be transparent and justifiable towards public policy makers and society in general. This means that when MCDM methods are used, these need to be transparent as well. For the assessment of strategies often transport models are used. Although the output of such models is exact (at least of a single run), these models are associated with uncertainty related to input data, behavioral models and externality models. This uncertainty can be large (over 10%), but is probably smaller in comparisons between solutions, because the assessment of the solutions are based on the same assumptions. This uncertainty can be part of the assessment procedure (e.g. by conducting sensitivity analysis), but in practice this is rarely done. Whether uncertainty is or is not reckoned with in the assessment of solutions, decision support methods like pruning methods and ranking methods should take the existence of this uncertainty into account.

Pruning and ranking methods as well as the analysis of the Pareto optimal set can be used as a basis of an interactive decision support tool to choose the best compromise solutions. Although the elements and methods are described in this chapter, the possible general framework of such support tool presented in Figure 6.3 is not explicitly tested in this research. The framework distinguishes four steps (i.e. general analysis, analysis main choices, choosing best compromise solutions and analysis best solutions). The general analysis of the Pareto optimal set and analysis of the main choices using pruning methods are incorporated to learn about the problems and solutions. Choosing the best compromise solutions using ranking methods, provides a set of solutions that should be closer investigated and within analysis of best compromise solutions the single best compromise solution is chosen. The main input of this interactive decision support tool is the Pareto optimal set. Other external input (left side Figure 6.3) is related to the decisions needed. The outcome of the general analysis is about the relation between the objectives, the upper and lower bounds, the optimal designs and trade-offs. After the general analysis the main choices are closer investigated, possibly using pruning methods and using thresholds (e.g. introducing outcome constraints like maximum of accepted total CO_2 emissions) to reduce the Pareto optimal set further. After that, the Pareto optimal set (complete or reduced set) is ranked using ranking methods and weighting factors, resulting in the best compromise solutions. These solutions are closer investigated, possibly using additional criteria like equity or complexity to choose the best compromise solution or to derive a general strategy. The output of every step is input for the next in which it can be input for decision makers, to be able to formulate thresholds or weighting factors, or inputs for the analysis or choices (i.e. pruned Pareto optimal set and best compromise solutions). Note that the input related to the decisions needed is connected with a line with two arrowheads. This represents the interaction to learn about the consequences of choices made (e.g. to conduct sensitivity analysis on the used weighting factors).

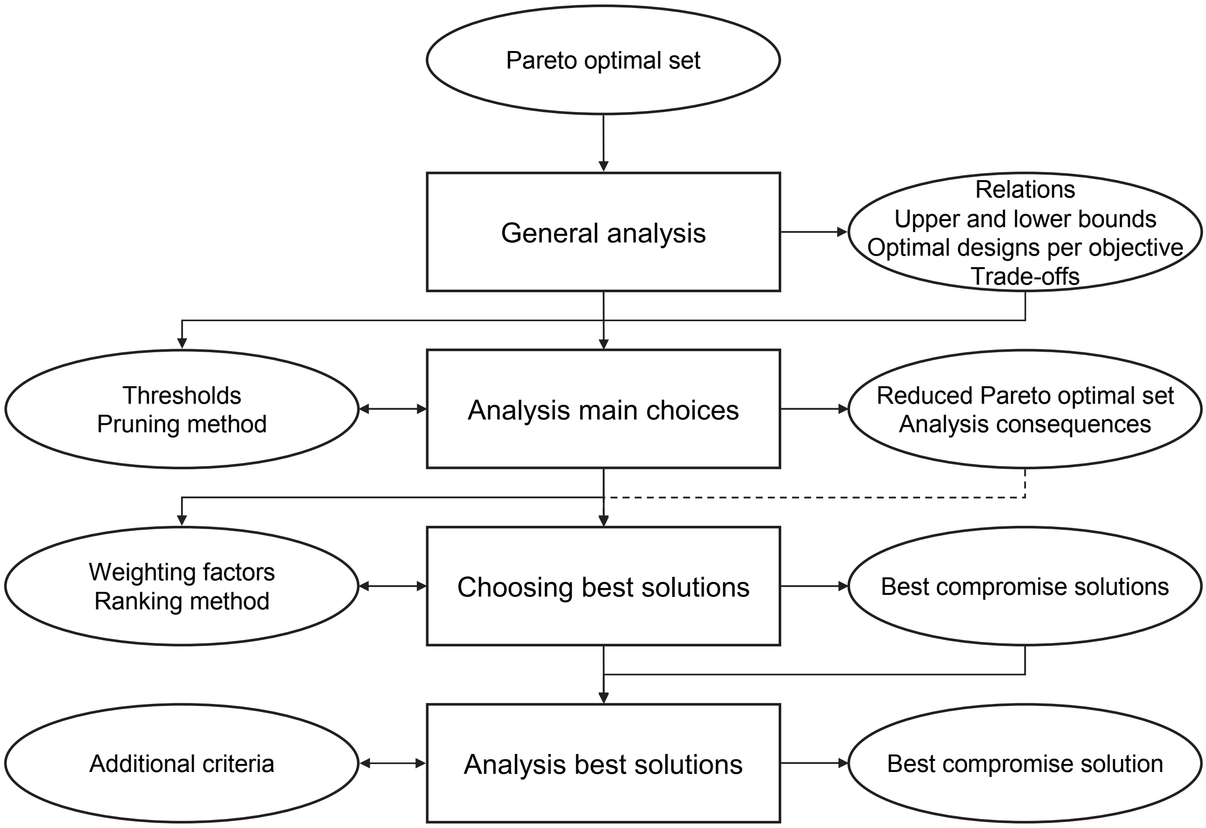

Figure 6.3 Framework decision support tool

In this chapter the information contained by the Pareto optimal set is described and the way this can support the decision making process. Then methods are discussed and applied to prune the size of the Pareto optimal set and methods to rank the solutions of the Pareto optimal set to demonstrate the various outcomes, advantages and disadvantages.

6.2 Information contained by Pareto optimal set

The Pareto optimal set contains valuable information for the decision making process, which is not available if the compensation principle would be chosen in advance (e.g. turning the MO NDP into a SO NDP using a weighted sum). The following issues are addressed:

- Information on how the objectives are related (i.e. opposed or aligned)
- The lower and upper bound and connected optimal designs
- Trade-offs and sensitivity
- Mapping solution and objective space

Before addressing these issues the concept of optimal design per objective is explained. An optimal design for an objective represents the optimal solution S_i^* for a certain objective i, which means the deployment of DTM measures that results in the minimal outcome of an objective i:

$$S_i^* = \arg\min_{S} z_i \tag{6.1}$$

Relation
The Pareto optimal set provides information to what extent the objectives are opposed or aligned. If all considered objectives are aligned, the decision is relatively easy, because then it is (almost) possible to optimize all objectives simultaneously (i.e. optimal designs per objective are similar). However, if these are opposed explicit decisions are needed. In theory it is possible that the objectives are completely aligned or opposed. See for example Figure 6.4 in which for one (continuous) decision variable and two objective functions, both to be minimized, it is shown what the results are in this case. When the objectives are completely aligned, there is one solution that can be identified as the optimal solution for both objectives. However, when the objectives are completely opposed the opposite is true and all solutions are part of the Pareto optimal set.

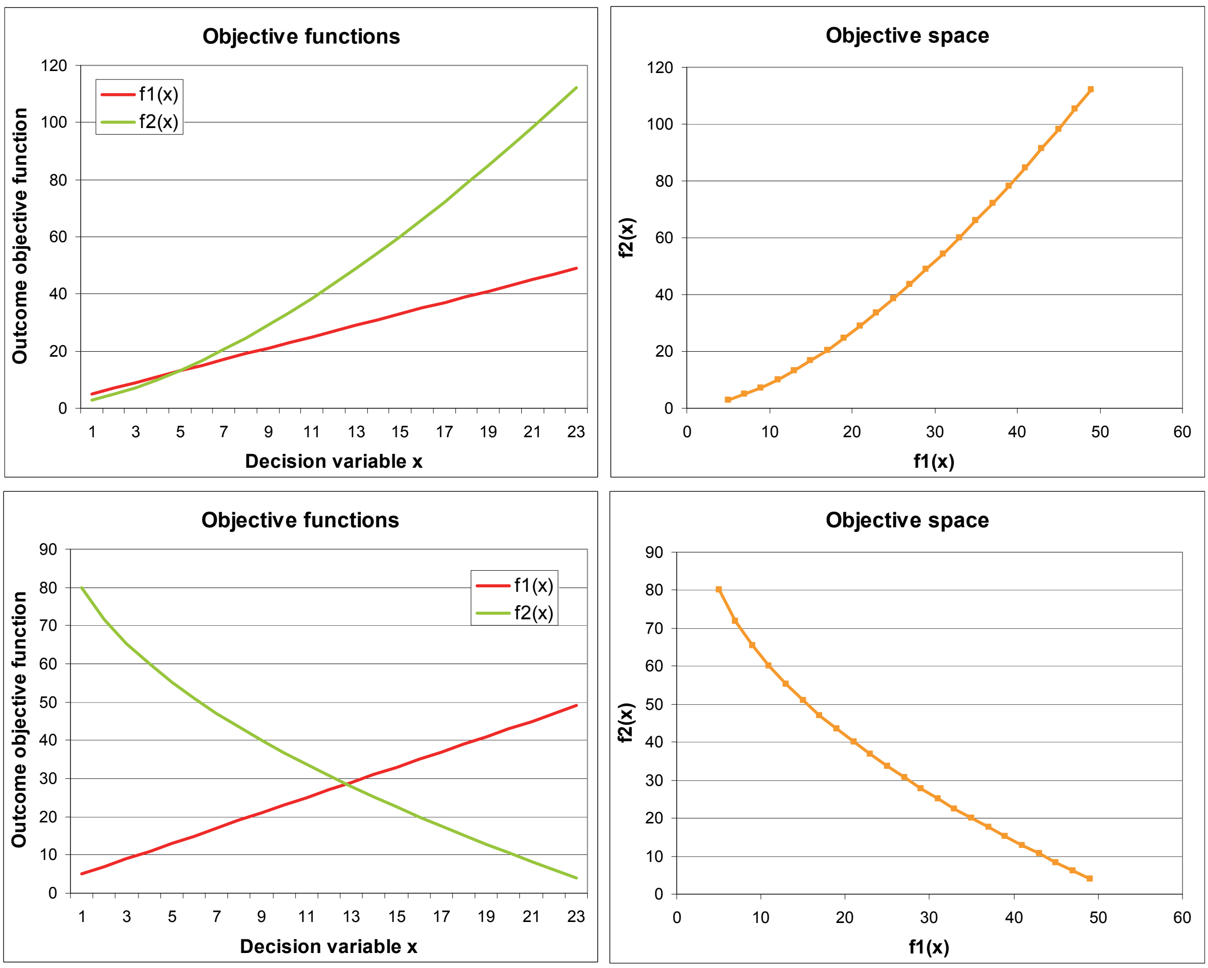

Figure 6.4 Completely aligned versus completely opposed

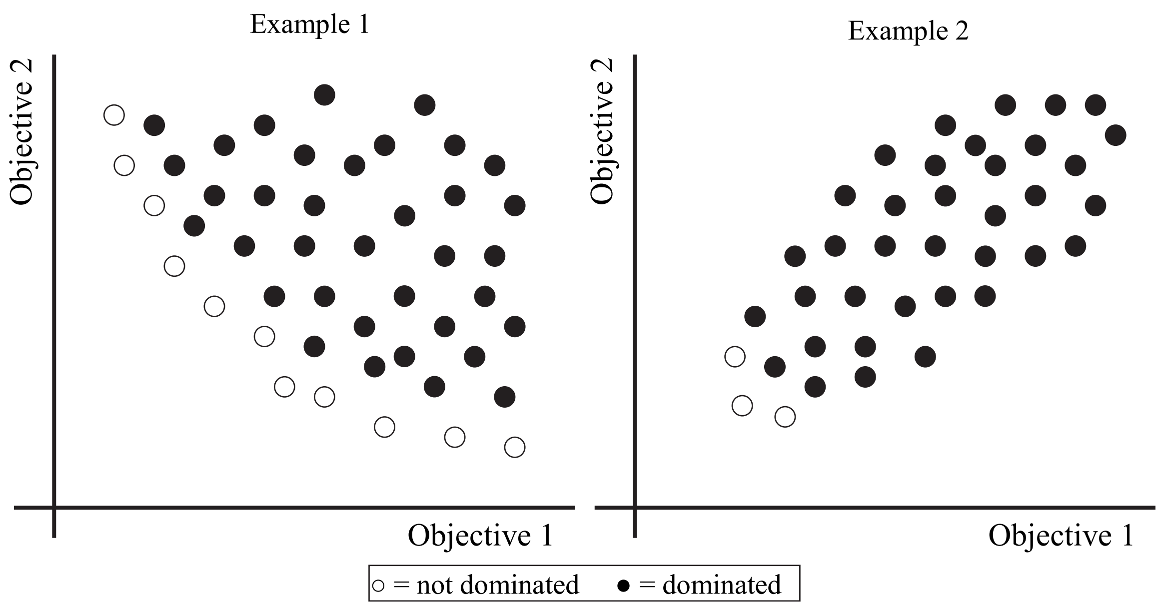

Figure 6.5 Examples of a Pareto optimal set

Often this will not be the case, meaning that there will be dominated and non-dominated solutions. In Figure 6.5 two hypothetical examples of a Pareto optimal set resulting from a bi-objective minimization problem are presented. The first example shows a large spread Pareto front in which the best performing solutions for one objective are the worst performing solutions on the other objective. In example two this is not the case, the best performing solutions for one objective are also the best scoring solutions on the second objective. Example 1 shows that these two objectives are highly opposed, while example 2 shows that these two objectives are highly aligned. Once a MO NDP is solved the Pareto optimal set is known and therefore information is available to what extent the various objectives are aligned (i.e. can be optimized simultaneously) and to what extent these are opposed (i.e. decisions are needed to weigh these objectives). Note that the information as presented in Figure 6.5 is only available if also dominated solutions are assessed. Because heuristics are needed to solve the MO NDP, also dominated solutions will be assessed. However, if there would exist an analytical solution to determine the Pareto optimal set, only the non-dominated solutions would be known. In that case only the number of solutions part of the Pareto optimal set and the distances between the upper and lower bound would provide an indication of the relation between the objectives.

Lower and upper bound

The Pareto optimal set contains the lower bounds per objective and the upper bounds given the other considered objectives (assuming all objectives being minimized). This means that the upper bound is not necessarily the worst performance for that objective (see for example Figure 6.5, example 2). The lower and upper bound provide information to what extent DTM measures can be used to influence certain objectives. If the performance of a reference solution is known, the lower and upper bounds also provide insights in the extent in which this reference situation can be improved. The optimal solution per objective is therefore also known, which is called an optimal design for a specific objective. In this research in which all objectives are minimized the performance of the optimal design equals the lower bound. The lower and upper bounds can be used within the decision making process to facilitate the possible determination of thresholds for certain objectives (e.g. total emissions should not exceed the current emissions (reference case)) and shows what the consequences are. If the decision maker is capable of defining ambitious but achievable thresholds, this is already a possible way to reduce the Pareto optimal set significantly. In Figure 6.6 the optimal designs are indicated, as well as an example of defining a threshold based on the reference case. The consequence of setting this threshold also means that the feasible optimal design of objective 1 changes, and is no longer the solution related to the lower bound of the original Pareto optimal set.

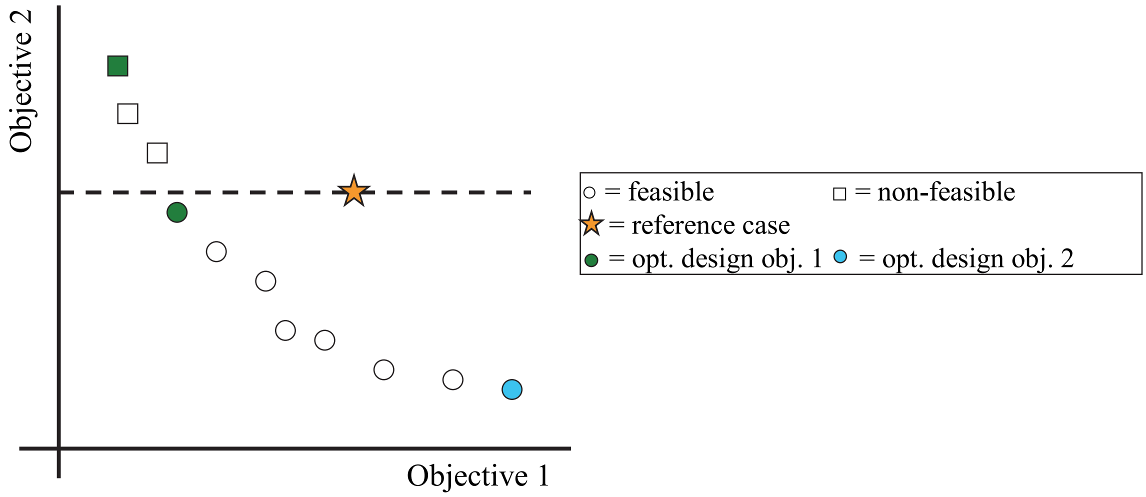

Figure 6.6 Examples upper and lower bounds

Trade-offs

The trade-offs represents how much an increase in one objective has to be accepted to improve another objective with a certain amount, when moving from one solution to another (e.g. it is possible to reduce emissions with amount x, but this means an increase in number of injuries of y). If more than two objectives are considered, there are multiple aspects that can gain or lose when comparing two solutions. Note that when comparing two solutions part of the Pareto optimal set, there is at least one objective that gains and one objective that loses. The impacts at other objectives are related to the level in which the different objectives are aligned or opposed. The calculation of a trade-off is the ratio between the difference in one objective and the difference in another.

$$Trade-off_{S_{j1},S_{j2}}\left(z_{i1},z_{i2}\right)=\frac{z_{i1}\left(S_{j1}\right)-z_{i1}\left(S_{j2}\right)}{z_{i2}\left(S_{j1}\right)-z_{i2}\left(S_{j2}\right)} \tag{6.2}$$

If there are more than one objectives involved, there exist a vector of trade-offs that can be positive or negative describing these gains and losses when moving from one solution to another. These trade-offs are related to the compensation principle, which is needed to choose the best compromise solution. If a compensation principle is used in which the objectives are linearly weighted, it is possible to draw contour lines (bi-objective case) that represent the line on which the final outcome of the weighted sum is exactly the same (see Figure 6.7, example 3). The slope of the contour lines is identical with the trade-off decision makers are willing to accept (i.e. compensation principle). This way the best scoring solution can be visualized, which is the solution lying on the contour line with the lowest value. For realistic optimization problems, the solutions part of the Pareto optimal set are in general not situated on a perfectly convex line, which is also not the case in the example. This means that, independent of the weighting used, some of the solutions part of the Pareto optimal set will never be the best scoring solution (see Figure 6.7, example 4). In the extreme case in which the Pareto optimal solutions are situated on a perfectly concave line only the optimal solutions for the single objectives are possibly the best scoring solutions. The convex hull connects the solutions that can possibly be chosen when linearly weighting is used. This provides information on the sensitivity for the weighting used, because it shows how much the weighting has to change to end up with a different optimal solution.

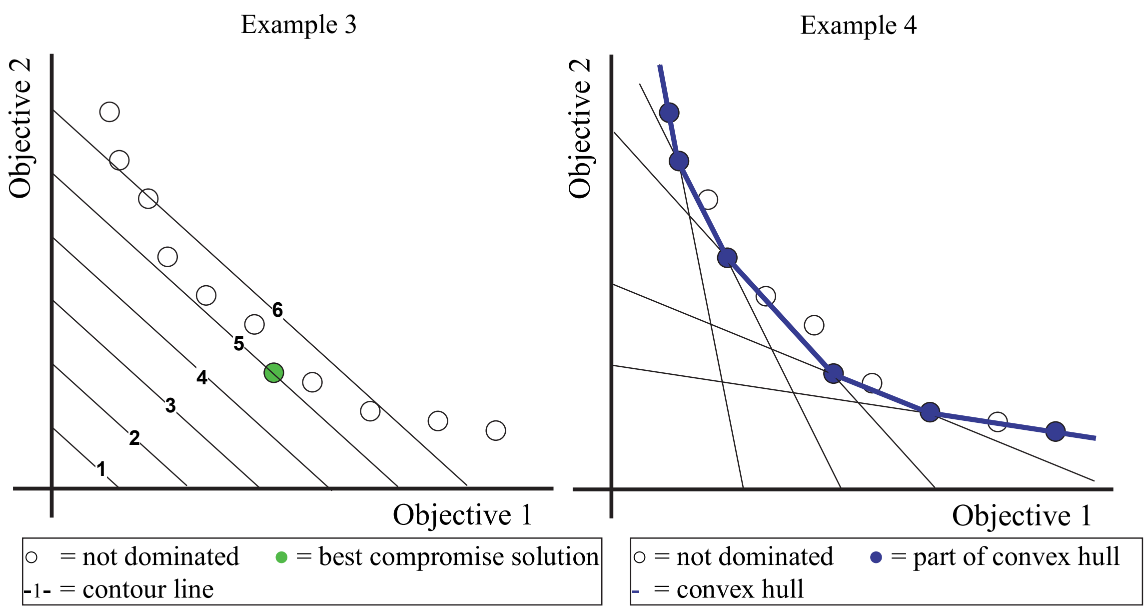

Figure 6.7 Linear weighting of the objectives

Trade-offs are calculated by comparing the performance of two solutions. The average trade-off can be determined by using the optimal designs for the single objectives and provides knowledge on the possible effects. This average trade-off represents the compensation principle (i.e. weighting factors) in which these two objectives are equally weighted (assuming normalization based on optimal designs). However, for all combinations of solutions part of the Pareto optimal set the trade-offs can be determined. In Figure 6.8 a hypothetical case is presented of Pareto optimal solutions. Trade-off one shows that if an increase of 5 kTon of CO_2-emissions is accepted it is possible to reduce travel times with 40 hours and vice versa (trade-off of 0.125 KTon/h and 8 h/KTon). The average trade-off (i.e. trade-off 2) in this hypothetical case is on average 10 hours for 1 kTon CO_2-emissions. Note that the trade-offs are limited by the solutions itself (i.e. these are the boundaries).

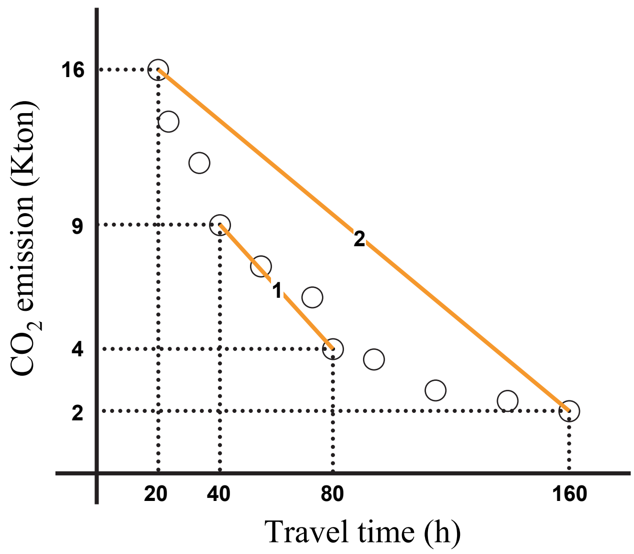

Figure 6.8 Trade-offs

The trade-offs however between all solutions part of the Pareto optimal set are valuable for the decision making process, because it makes choices tangible (i.e. is a certain deterioration of an objective accepted to gain an improvement in another). This can be used interactively with the decision makers to determine a suitable compensation principle. Depending on the preferences of the decision maker, it is for instance possible to start with the reference situation (or any feasible solution) and by comparing this solution with others, determining the trade-offs that are acceptable and those that are not. Choosing the best compromise solution can therefore be based on comparison with a reference solution. However, this reference solution for the current situation is not necessarily part of the Pareto optimal set and in current practice externalities are not yet explicitly part of the objectives to determine traffic management strategies. Choosing the best compromise solution based on which solutions can improve all objectives compared to the reference case, would mean that the externalities are still not equally taken into consideration (compared with efficiency). In addition, if strategies are sought for a forecast year additional assumptions are needed about a reference strategy for the future. Because in this research additional objectives compared to current practice are considered, using a reference solution that probably solely focuses on optimizing efficiency, possibly limits the scope of the decision makers. Although knowledge about the differences between a certain strategy and a reference is of interest and should and can be taken into account in the decision making process, it is assumed that decision makers have to choose the best compromise solution given the Pareto optimal set providing all possible options.

Mapping solution and objective space

It is not necessarily true that solutions that are close to each other in objective space, are also close to each other in solution space even though the settings of the DTM measures are defined on an interval scale. This is especially true when the objective functions are formulated as network performance functions, which is the case in this research. This means that it is possible that two totally different DTM strategies result in similar performance on the objective functions and vice versa. This can be illustrated by a simple network with two similar routes between an origin and destination and assuming that it is possible to meter traffic on both routes. In that case, metering traffic on route 1 will result in similar outcome on the network performance functions as metering traffic on route 2, although the strategy is completely different. In addition, it is also possible that Pareto optimal solutions can be found in all parts of solution space. In Figure 6.9 a hypothetical example is shown in which there are two decision variables and two objective functions, to illustrate a possible mapping. Another reason is that the impact of changing a setting of one DTM measure can be much larger than changing the setting of another, although in solution space the difference is equal (e.g. closing a rush hour lane on a saturated road versus increasing capacity of a certain direction with free flow conditions). This knowledge is of interest, because then it is possible to choose the best comprise solution out of a set of solutions that perform similar on the objective functions based on additional criteria like equity or complexity of the measures needed. Note that this also means that it is probably better to use the complete Pareto optimal set in the ranking step of the decision support tool and to choose a set of best compromise solutions to investigate closer. In addition, it is also true that there can be measures for which the outcome of the objective functions is highly sensitive and analyzing this sensitivity is of importance in the closer investigation and the eventual translation of a strategy into the actual deployment of DTM measures on operational level.

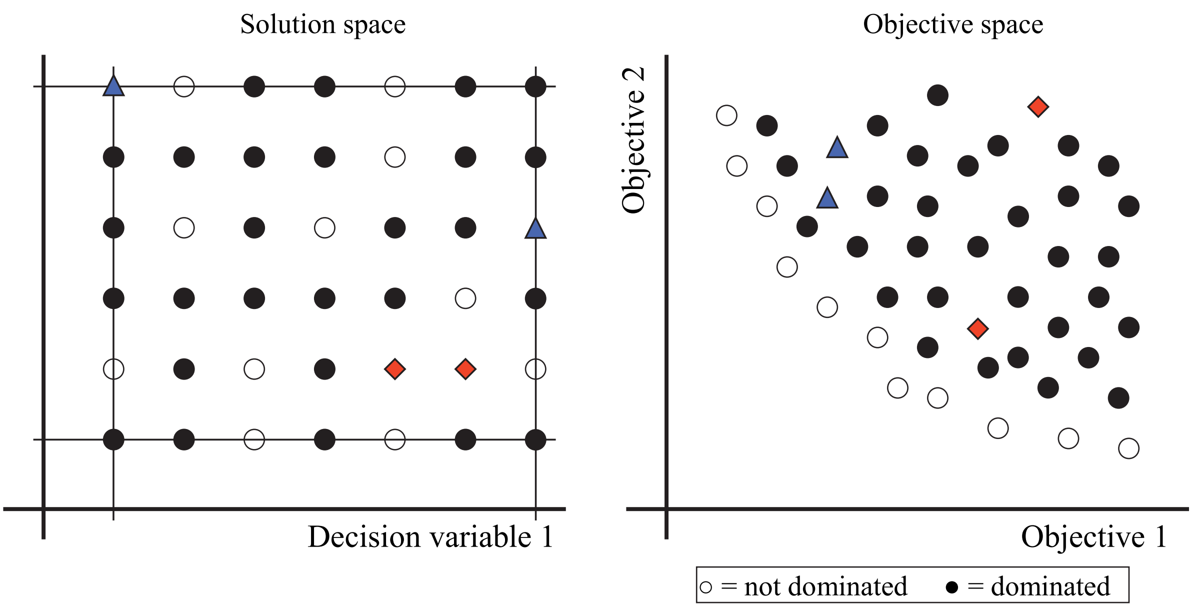

Figure 6.9 Mapping solution and objective space

To illustrate that solutions close to each other in solution space are not necessarily close to each other in objective space, the outcome of all evaluated solutions for one single run, optimizing the objectives noise and efficiency using SPEA2+ for case 1 (see Chapter 4), is presented in Figure 6.10. In this case all solutions are clustered in solution space and the resulting 10 clusters are plotted in objective space. Although the solutions in a cluster do show a correlation, it also shows that solutions in one cluster can result in low as well as high values for the objective functions and that solutions in two distinct clusters can be situated close to each other in objective space.

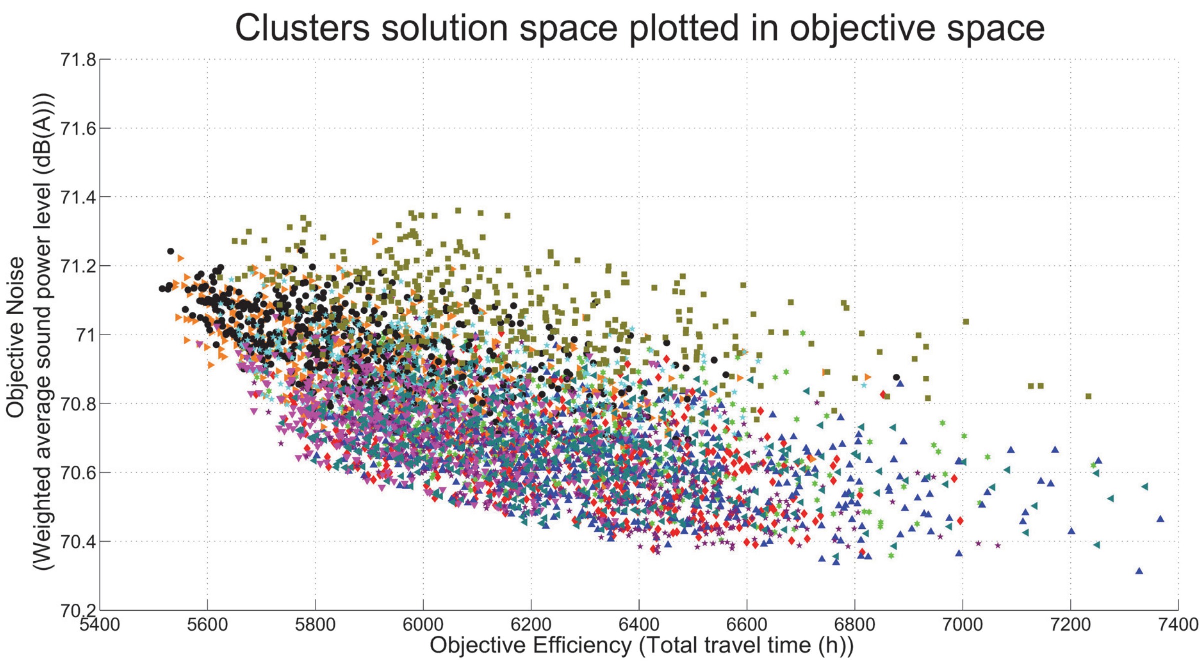

Figure 6.10 Clusters solution space plotted in objective space

The discretization used in solution space also influences the Pareto optimal set of solutions that can be found, because this also results in a discrete picture of the Pareto optimal set. As a consequence it is also possible that gaps exist in the found efficient frontier, which would not exist when a continuous decision variable is assumed. In this research only discrete decision variables are used of which some are continuous and some are discrete in reality. Especially the existence of discrete decision variables related to large changes in supply of infrastructure (e.g. opening or closing a rush hour lane), can result in such gaps. Knowledge on the existence of these gaps and the related decision variable(s) is of interest for the decision making process. First of all, to know whether it is probably true that there are feasible solutions that are situated in this gap. If this is true and these areas are of interest for the decision making process, additional runs can be done using a finer grid for specific parts of the solution space. Second, it can feed the discussion on choosing the best compromise solution, because often the separated parts of the efficient frontier will be connected with distinct measures and traffic conditions.

6.3 Pruning

6.3.1 Introduction

As indicated in the introduction of this chapter, the Pareto optimal set of solutions can become large and as a consequence difficult to analyze and to comprehend. In this case pruning can be applied to reduce the Pareto optimal set to assist the decision maker, which makes it possible to provide a comprehensive analysis of the main choices for the decision makers. The pruning methods are basically filters that select the most relevant Pareto optimal solutions. For pruning methods there is little literature available. The topological method developed by Russo and Vitetta (2006) is one of the rare researches available on application of pruning methods for MO NDP. In their research a clustering method is used to cluster solutions in solution space and subsequently they selected a representative solution for each cluster. Although clustering is a possible option to prune the Pareto optimal set, clustering in objective space makes more sense to be able to present decision makers the main choices. In (Wismans et al., 2010) the convex hull method used in this research is applied on the outcome of the dynamic MO NDP for case 1 (see Chapter 4) and in (Brands et al., 2012) the practically insignificance trade-off (PIT) filter, developed by Mattson et al. (2004), is improved (PIT-2) and applied on the outcome of the dynamic MO NDP for the same case. Taboada et al. (2007) developed the non-numerical ranking preference filter and data clustering filter and applied these in conjunction on the redundancy allocation problem. Sleesongsom (2008) developed the even Pareto filter on a hypothetical bi-objective optimization problem. This even Pareto filter is closely related to truncation procedures incorporated in EMOA to retain diversity within the set of parents solutions.

6.3.2 Pruning methods

Pruning methods reduce the number of solutions within the Pareto optimal set, while retaining the main characteristics of this set. As indicated this pruned Pareto optimal set should contain the solutions that show significance differences, the extremal solutions and an equal spread along the efficient frontier. The pruning methods are basically filters that can possibly also be used within EMOA if truncation is needed. The methods selected are convex hull filter, PIT filter and *k*-means clustering filter, which are basically the types of methods available for which no additional information of the decision makers related to the compensation principle (e.g. priorities in objectives) or number of solutions that should remain after filtering is necessary.

The convex hull filter (Wismans et al., 2010) assumes that within the decision making process the objectives are eventually linearly weighted. In that case, some of the Pareto optimal solutions are irrelevant and never chosen as the final (best scoring) design. The only relevant solutions are part of the edges of the convex hull, and selected by this method. The convex hull filter can be effective, but it does not guarantee a reduction of solutions, an even spread of solutions in the objective space and assumes certainty concerning the performance of the solutions.

The method using the practically insignificant trade-off (PIT) filter (Mattson, 2004) assumes that within the decision making process the regions of the Pareto frontier that entail significant trade-off are the most interesting. In this pruning method the user has to define insignificant trade-off per objective, which is related to the data quality and the range of the effects possible. This is operationalized by two parameters. Δ^1 specifies the insignificance: if two solutions differ less than Δ^1 from each other in one objective, the two solutions are considered as equal on that objective. Δ^2 specifies the minimum level of spread along the Pareto front: if two solutions differ more than Δ^2 they are considered to be different. This parameter is needed if it is desirable that no big gaps exist in the Pareto front. Note that Δ^2 is always greater than or equal to Δ^1 and that the solutions are sequentially evaluated, often with an extremal solution as starting point. In the bi-objective case, this means that the regions of practically insignificant trade-off are formed by Δ^1 in one direction and Δ^2 in the other for each solution. Other solutions that fall within these regions, are removed. The order in which the solutions are assessed in the algorithm, influences the outcome of this filter. This method can be effective and guarantees a representation of the complete Pareto frontier. The original method (called smart Pareto filter) by Mattson is improved in (Brands et al., 2012) and called PIT-2. PIT-2 guarantees preservation of extreme solutions and treats insignificance correctly by defining insignificance in more than one dimension in the case of more than two objectives. This PIT-2 filter is used in this research. However, depending on its parameters this method does not guarantee a reduction of solutions or an even spread of solutions. Furthermore, the starting solution of the algorithm influences the possible selection procedure.

The clustering method (Taboada et al., 2007; Handl and Knowles, 2007) assumes that within the decision making process distinct solutions in the objective space are relevant. In this pruning method a data mining clustering technique is used to cluster similar solutions, while the number of clusters is optimized. The *k*-means clustering method, which is used in this research, minimizes the within cluster variance. For each cluster, one representative solution is chosen in which often the solution nearest to the center of the cluster j is used. To optimize the number of clusters, an additional objective is used: the average silhouette width. The silhouette width Θ evaluates the clustering validity. For every solution, it calculates the average distance to all other points in its cluster $a(j)$ and the average distance to all other points in the nearest neighbor cluster $b(j)$.

$$\Theta(j) = \frac{\left(b(j) - a(j)\right)}{\max\left\{a(j), b(j)\right\}} \qquad 6.3$$

If the silhouette value is close to 1, it means that the solution is well clustered and it was assigned to a very appropriate cluster. If the silhouette value is about zero, it means that the solution could be assigned to another closest cluster as well and if it is close to -1, it means the solution was misclassified. The overall silhouette width is the average of the silhouette values of all solutions. The largest silhouette width indicates the best clustering. Therefore, the number of clusters associated with this best clustering is taken as the optimal number of clusters. This method is effective in reducing the number of solutions, given that at least one cluster of more than one solution is created (Handl and Knowles, 2007). Note that the average silhouette width will always be best if the number of clusters equals the total number of initial solutions. However, it does not necessarily guarantee an even spread of solutions, is sensitive for outliers (because these influence the mean of each cluster) and the selection of the representative solution is arbitrary. To avoid ending up in a local optimum as a result of the randomly chosen initial cluster centers, the method is repeated multiple times.

6.3.3 Application pruning methods

Set up application

To illustrate the pruning methods, case 2, which is described in chapter 4, and all objectives are used. The MO NDP is solved using the NSGAII algorithm in which the archive size $W_u = 250$ and number of generations $H = 50$, resulting in 12,500 evaluated solutions after the initialization. The initial mutation $\rho_{mut}^{init} = 0.05$, which decreased every generation with 5% for the first 10 generations. The methods presented are applied using all Pareto optimal solutions $X^* = \left\{S_1^*,..,S_j^*\right\}$, found by the optimization process (i.e. the total Pareto optimal set) as well as using only the final generation of this process (i.e. the final Pareto optimal set). Both, within the PIT filter and within *k*-means clustering parameter settings are needed. To operationalize insignificant trade-off in the PIT filter, two parameters are defined. Δ^1 specifies the insignificance: if two solutions differ less than Δ^1 from each other in one objective, the two solutions are considered as equal on that objective. Δ^2 specifies the minimum level of spread along the Pareto front: if two solutions differ more than Δ^2 in any objective they are considered to be different. Several choices of these parameter settings are evaluated, because these additional parameters influence the outcome. For the *k*-means clustering filter a maximum number of clusters to be considered should be set, because otherwise the number of clusters equal to the total number of initial solutions will perform best.

Application

All pruning methods are able to reduce the Pareto optimal set significantly. In Table 6.1 the results are presented, using the methods to prune the total Pareto optimal set found during the optimization process (4179 solutions) and the final Pareto optimal set (250 solutions). Figure 6.12 presents the results for the total Pareto optimal set, in which for the PIT filter the results are shown for $\Delta^1 = 0.1$ and $\Delta^2 = 0.5$.

Table 6.1 Results pruning methods

			Size Pareto optimal set			
	Δ^1	**Δ^2**	**Absolute**	**Index**	**Absolute**	**Index**
Initial size			250	100.0	4179	100.0
Convex hull filter			92	36.8	270	6.5
PIT filter	0.05	0.20	127	50.8	481	11.5
	0.05	0.50	129	51.6	441	10.6
	0.10	0.20	53	21.2	108	2.6
	0.10	0.50	47	18.8	81	1.9
Clustering filter			5	2.0	120	2.9

The *k*-means clustering filter results in the smallest set of 2%. However, analyzing the silhouette width of the different number of clusters shows that there is not a number of clusters for which there is a clear better or worse performance (see figure 6.11). In this case there are no distinct clusters within the total set and optimization of the number of clusters is arbitrary. This could possibly be expected for the final Pareto optimal set of 250 solutions, because the NSGAII algorithm aims at an even distribution of solutions along the efficient frontier. However, similar results are also found for the total Pareto optimal set. This means that the chosen discretization has therefore not resulted in distinct gaps in the efficient frontier. Because, there are no distinct clusters, this method is not useful as pruning method in which the number of clusters is optimized, but can still be used to prune the set by presetting the number of clusters (i.e. number of solutions) to retain. However, if it is preferred to choose a subset for the ranking procedure based on this clustering method, there are some issues to solve regarding choosing the representative solution from a cluster. If the solution nearest to the center of the cluster is used, it is possible that some clusters are not taken into account in the ranking procedure when linear weighting is used, because these solutions are not necessarily part of the convex hull. This is also illustrated in Figure 6.12 comparing the selected solutions by the *k*-means clustering filter with the selected solutions by the convex hull method. This means that this method can be used to present the decision makers the main choices, but it is not recommended to use this reduced Pareto optimal set within the ranking procedure.

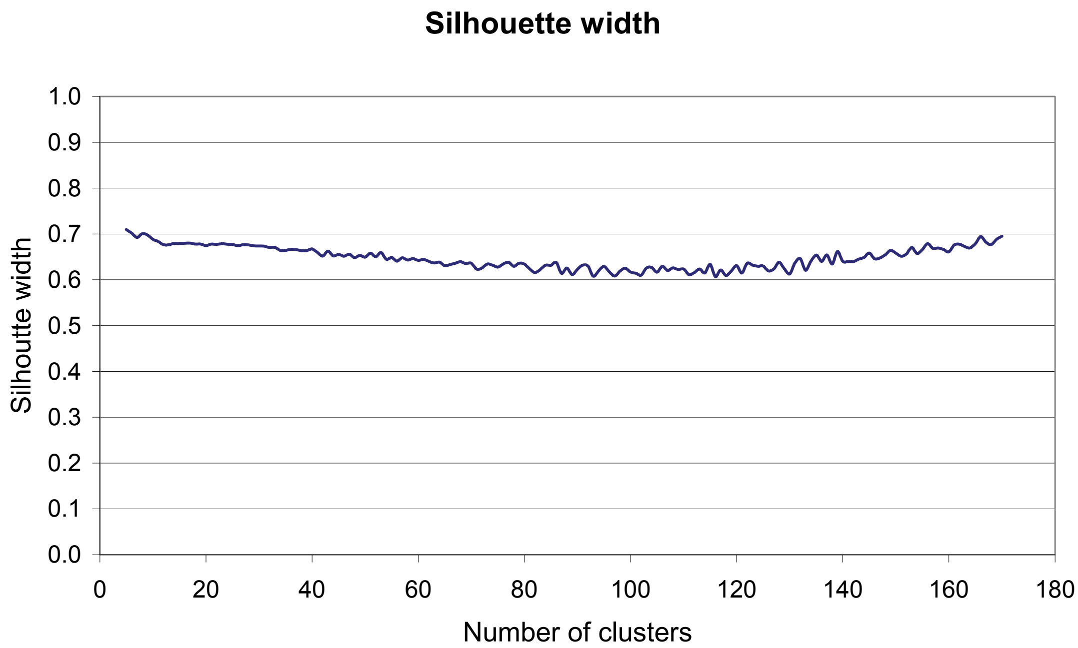

Figure 6.11 Silhouette widths dependent on number of clusters (final Pareto optimal set)

The convex hull filter results in a remaining Pareto optimal set of 37% in this example. Earlier application of this method in Wismans et al. (2010) showed that when three objectives are simultaneously optimized, the Pareto optimal set was on average reduced to less than 25% of the original size. However, the effectiveness of this method depends on the extent in which the solutions part of the Pareto optimal set are situated on a convex line in objective space. (i.e. if all solutions are situated on a convex line, then all solutions are part of the convex hull). Furthermore, if there is a large reduction, it is likely that large areas in the objective space are not considered in the resulting pruned set. Because this method assumes that linear weighting is used to choose the best solution, it has the drawback of assuming the outcome of the solutions on the various objectives to be exact.

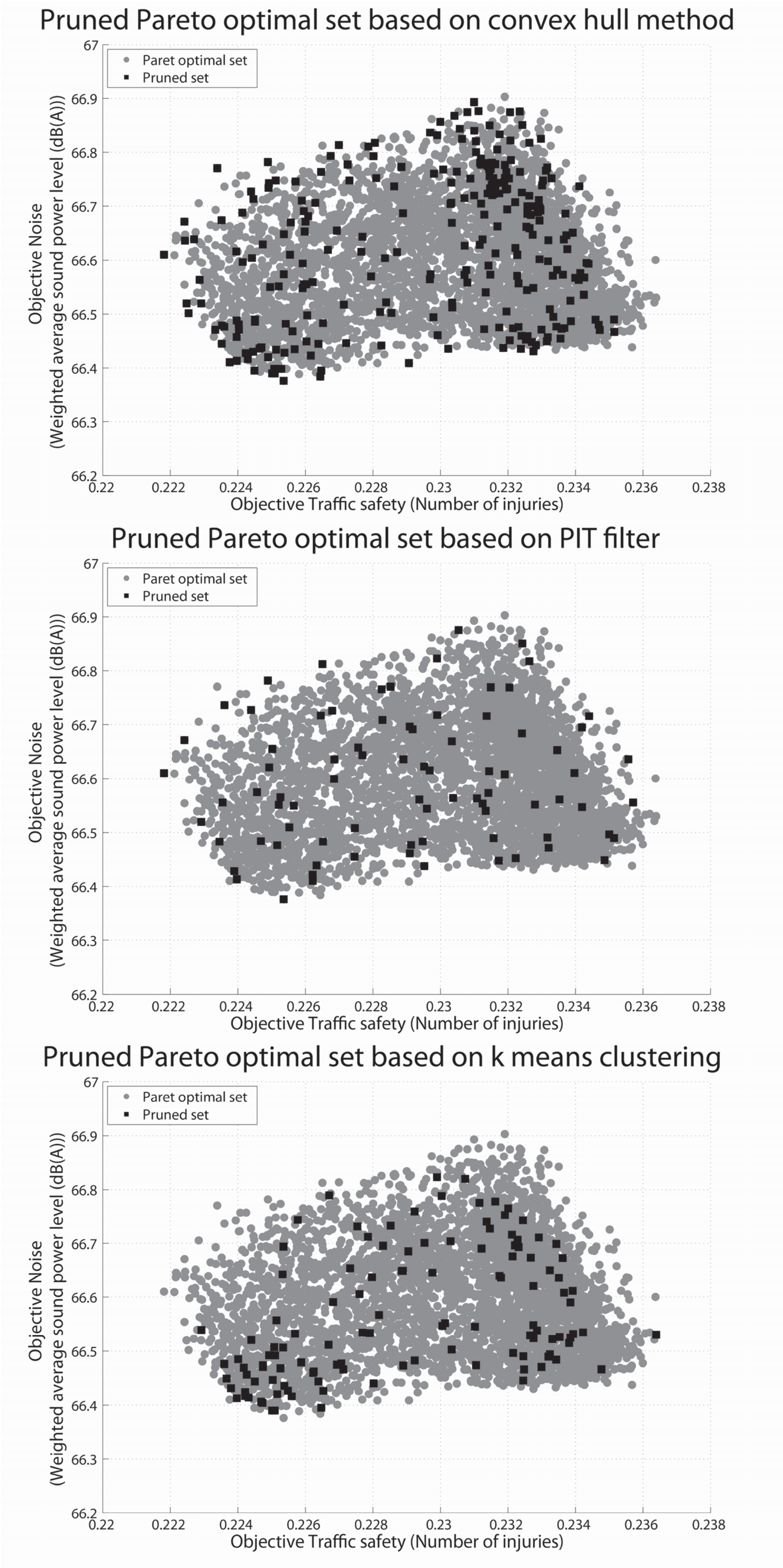

Figure 6.12 Outcome pruning methods

The PIT filter can reduce the original set size significantly as well. The outcome of this method depends on the used settings for insignificance Δ^1 and minimum level of spread along the Pareto front Δ^2, and offers the possibility to address the uncertainties regarding the exact outcomes of the objective function or to influence the level of pruning directly. Similar with the *k*-means clustering filter, the PIT filter can possibly prune solutions part of the convex hull and retain solutions that are not. The advantage of this method is that it aims at retaining the solutions that show significant differences and therefore will retain more solutions in areas in which the trade-offs between the solutions change. Setting the parameters can be used to control the outcome of this process. These solutions are the interesting solutions for the decision making process. Furthermore, this PIT filter results in this case also in a more equal spread of retained solutions as illustrated in Figure 6.12. This method is therefore a more suitable method than the other presented methods when the reduced set is used within a ranking method (i.e. to choose a subset).

6.3.4 Conclusions

Pruning methods reduce the Pareto optimal set, retaining distinctive solutions as an input for the decision making process. Because in this case the Pareto optimal set shows an even spread, the *k*-means clustering filter results in arbitrary cluster sizes if optimized using the silhouette width. However, irrespectively if this is also the case in other situations, this method is useful to analyze the main choices by presenting the results in aggregated form to the decision makers. However, because choosing a representative solution for one cluster is not trivial, this method should not be used to select a subset of solutions. The convex hull filter can result in a significant reduction of the Pareto optimal set and is in accordance with ranking methods using linear weighting, but may result in neglecting interesting parts of the objective space. The PIT filter is the most suitable method to choose a subset, because it is related to the changes in trade-offs between solutions and therefore retains the interesting solutions for the decision making process.

6.4 Ranking

6.4.1 Introduction

Ranking methods can be used to select the best compromise solutions that should be investigated further. There does not exist a method that is best in general and there is still an ongoing debate on this subject. Therefore, as indicated in the introduction of this chapter, the ranking method chosen should corresponds with the underlying decision process and is in accordance with the qualities of the data related to the presented MO NDP. In addition, it has to be transparent as well, because the decisions made, based on this method, need to be transparent and justifiable towards public policy makers and society in general.

There are numerous ranking methods described in literature, which can for example be classified according to the type of data they use (deterministic, stochastic or fuzzy). However, there may be situations that involve combinations of data types. All methods basically aim to rank the solutions by comparing the performance of these solutions on the individual objectives. The literature on MCDM is extensive. However, Tzeng and Tsaur (1997) is one of the rare applications in which a ranking method was applied to select a compromise solution after solving a MO NDP: the elimination et choix traduisant la realité III (ELECTRE III) method was used to select a compromise solution minimizing government budget and total travel time of road users by improving a metropolitan network. Iniestra and Gutierrez (2009) used an EA to determine the Pareto optimal set of combinations of transportation infrastructure projects given a budget constraint. They formulated the problem as a multi-objective 0-1 knapsack problem and used ELECTRE III to select the optimal combination. However, within traditional traffic and transport research in which a number of predefined solutions are compared, several MCDM methods are used. Grassini and Viviani (2005) for example used the preference ranking organization method for enrichment evaluations (PROMETHEE) to evaluate local transport service and Jaroenkhasemmeesuk et al. (2010) used the analytical hierarchy process (AHP) to select the best alternative towards a sustainable transport system.

6.4.2 Ranking methods

Ranking methods are basically MCDM methods. Some of these methods are also used for the fitness assignment step of evolutionary multi-objective algorithms. In this research these methods are used after obtaining a Pareto optimal set to rank the solutions within this set. Point of attention is that the ranking methods are possibly subject to rank reversals, especially when a subset of the Pareto optimal set is used (Triantaphullou and Mann (1989). Rank reversal is a phenomenon in which the MCDM method exhibits contradicting rankings when exposed to some test (e.g. top ranking changes when a new alternative is considered with worst performance on all objectives). Because in many methods the scores are normalized or mutually compared, the determination of the subset may influence the outcome of the ranking methods.

Cost benefit analysis is an often used MCDM method to select the best compromise solutions in practice for the appraisal of infrastructural investment decisions. Therefore it is often also used to reformulate a multi objective optimization problems in traffic and transport as a single objective optimization problem, to reduce complexity. This method is a variant of the weighted sum method (WSM) and monetizes the effects. This means that monetary values are used as weighting factors. However, the consequences of this method are rarely addressed and the availability of the Pareto optimal set makes it possible to investigate these consequences. Although it is often used, the monetary values are debatable because they are (partly) based on different assumptions and do not take into account the difficulty of reaching certain policy goals or the increasing marginal costs in reducing the externalities (Rothengatter, 2009; Mouter et al., 2011; MacKie, 2010; Sytsma, 2006).

CBA is possibly not the best suitable approach for the deployment of DTM measures and therefore also other methods may be of interest within a decision support tool. In this research the elementary methods weighted sum method (WSM) and weighted product method (WPM) are applied as well as the often used analytical hierarchy process (AHP) and the ELECTRE III method, which is an outranking method. These methods are chosen, because these are widely used also within the field of transportation (Macharis and Ampe (2007) and to cover most types appropriate for the data characteristics of the MO NDP, i.e. deterministic with a level of uncertainty. Additionally, the weighted average ranking (WAR) is chosen, which can be used as a fitness assignment within EMOA. In all ranking methods, weights can be used to consider the trade-offs between objectives and none of these ranking methods guarantees that there is only one solution with the best rank. Table 6.2 provides an overview of the methods.

The weighted sum method calculates the score WSM of each solution S_j by summing the (normalized) objective values $z_i^N(S_j)$ for each objective (Triantaphyllou and Mann, 1989; Tryantaphullou et al., 1998). Normalization in this research is done by scoring each solution on each objective between the maximum and minimum value within the Pareto optimal set. These normalized values can be weighted using relative weighting factors θ_i dependent on objective z_i.This is the traditional and often used ranking method within the multi-criteria decision analysis in which the objectives are linearly weighted. Normalization or same units of measurement for all objectives is necessary for this technique to assure each objective has more or less the same magnitude, if all objectives are equally weighted. However, the normalization procedure can introduce rank reversal. The lower the value of WSM, assuming all objectives should be minimized, the higher this solution is ranked. A variant of the WSM method is the also often used CBA in which the weights θ_i^M represent the economic trade-off between the objectives. Normalization is therefore not necessary, because all effects are translated into costs. Within this research the monetary values are derived from the Handbook on estimation of external costs in the transport sector, which is a product of the European project 'IMPACT' (Maibach et al., 2008). Point of attention is that all external costs use linear weighting (marginal costs) except for noise (average costs).

The weighted product method calculates the score WPM comparing two solutions S_{j1} and S_{j2} by multiplying a number of ratios, one for each objective (Triantaphyllou and Mann, 1989; Tryantaphullou et al., 1998). Each ratio is raised to the power equivalent to the relative weight θ_i depended of objective z_i. This method is dimensionless and normalization is not needed. If $WPM(S_{j1}/S_{j2})$ is smaller than one, then solution S_{j1} is more desirable than solution S_{j2}. This method tends to penalize poor performance on one objective more heavily than the WSM method and results in a matrix of comparisons. The ranking is based on the number of times the solutions are more desirable and the best alternative is the one that is better or at least equal to all other solutions based on the WPM-score.

Without decomposition of the MCDM problem into a system of hierarchies or using Saaty's fundamental scale of relative importance to quantify the performance of a solution on a certain criteria, the AHP method can be used to rank solutions based on their AHP score (Saaty, 2008; Tryantaphullou et al., 1998). This method is also dimensionless, however is sensitive for rank reversal. The lower the value of AHP the higher this solution is ranked. Alternatively, the revised AHP (AHP_{rev}) is proposed to reduce the influence of rank reversal, although it is not eliminated. In this method, normalization is done by using the maximum score, while in the original method this is done by using the average score (is equivalent for the sum of scores). The similarity between the AHP and WSM is evident. The main difference is related to the normalization that is needed in WSM and incorporated in AHP.

The average ranking method is similar to the WSM, but calculates the score WAR for each solution S_j by summing the ranks $\Upsilon_i(S_j)$ for each objective (Corne and Knowles, 2007). These ranks can be weighted using relative weighting factors θ_i depending on objective z_i. The advantage of this method is that it does not need exact information concerning the differences in objective values between two solutions. However, it does assume that the calculated values per objective do provide the exact ranking. The lower the value of WAR the higher this solution is ranked.

The ELECTRE III method is specifically designed to deal with inaccurate or uncertain data for ranking problems, by using thresholds of indifference and preference (Tszeng and Tsaur, 1997; Buchanan et al., 1999; Roy et al., 1986; Roy, 1991). This method tests the assertion if $S_{j1}\mathbf{S}S_{j2}$, meaning solution S_{j1} is at least as good as OR is not worse than solution S_{j2} using a concordance and discordance principle. The concordance principle requires that a majority of criteria, considering their relative importance, is in favor of the assertion. The discordance principle requires that the minority of criteria that do no support this assertion are not strongly against this assertion in terms of outcome in objective value and is taken into account by using a veto threshold. Within this approach a credibility matrix is produced, which assesses the strength of the assertion $S_{j1}\mathbf{S}S_{j2}$. Within this approach, three thresholds are used, the indifference threshold ω_i, the preference threshold ρ_i and the veto threshold υ_i, and relative weighting factors θ_i. Based on this credibility matrix using downward and upward distillation, the final ranking is determined.

Table 6.2 Overview ranking methods

Method		
WSM	$WSM(S_j)=\sum_i \theta_i z_i^N(S_j)$	6.4
CBA	$CBA(S_j)=\sum_i \theta_i^M z_i^N(S_j)$	6.5
WPM	$WPM(S_{j1}/S_{j2})=\prod_i \left(\frac{z_i(S_{j1})}{z_i(S_{j2})}\right)^{\theta_i}$	6.6
AHP	$AHP(S_j)=\sum_i \theta_i \frac{z_i(S_j)}{\sum_j z_i(S_j)}$	6.7
	$AHP_{rev}(S_j)=\sum_i \theta_i \frac{z_i(S_j)}{\max\{z_i(S_1),...,z_i(S_J)\}}$	6.8
WAR	$WAR(S_j)=\sum_i \theta_i \Upsilon_i(S_j)$	6.9
ELECTRE III	$CI(S_{j1},S_{j2})=\begin{cases}\Lambda(S_{j1},S_{j2}), \text{ if } d_i(S_{j1},S_{j2})\le\Lambda(S_{j1},S_{j2}),\forall i\\ \Lambda(S_{j1},S_{j2})\prod_{i\in I, I=\{i\mid d_i(S_{j1},S_{j2})>C(S_{j1},S_{j2})\}}\frac{1-d_i(S_{j1},S_{j2})}{1-\Lambda(S_{j1},S_{j2})}\end{cases}$, in which $\Lambda(S_{j1},S_{j2})=\sum_i \theta_i c_i(S_{j1},S_{j2})$ and $c_i(S_{j1},S_{j2})=\begin{cases}1, & \text{if } z_i(S_{j1})-\omega_i\le z_i(S_{j2})\\ 0, & \text{if } z_i(S_{j1})-\rho_i\ge z_i(S_{j2})\\ \frac{\rho_i+z_i(S_{j2})-z_i(S_{j1})}{\rho_i-\omega_i}, & \text{otherwise}\end{cases}$ $d_i(S_{j1},S_{j2})=\begin{cases}0, & \text{if } z_i(S_{j1})-\rho_i\le z_i(S_{j2})\\ 1, & \text{if } z_i(S_{j1})-\upsilon_i\ge z_i(S_{j2})\\ \frac{z_i(S_{j1})-z_i(S_{j2})-\rho_i}{\upsilon_i-\rho_i} & \text{otherwise}\end{cases}$	6.10

6.4.3 Application ranking methods

Set up application

To illustrate the ranking methods, case 2, which is described in Chapter 4, and all objectives are used. The MO NDP is solved using the NSGAII algorithm in which the archive size $W_u = 250$, number of generations $H = 50$, resulting in 12,500 evaluated solutions after the initialization. The initial mutation $\rho_{mut}^{init} = 0.05$, which decreased every generation with 5% for the first 10 generations. The methods presented are applied using the final generation of the optimization approach (i.e. the final Pareto optimal set). Within all ranking methods, except for the CBA method, relative weighting factors θ_i are used, which are varied to illustrate the differences between the methods. The monetary values θ_i^M used in the CBA method are based on the European IMPACT study (Maibach et al., 2008) and presented in Table 6.3. The ELECTRE III method also needs additional parameters related to the indifference (ω_i), preference (ρ_i) and the veto (υ_i) thresholds. The first threshold mainly depends on the uncertainties related to the used traffic models and externality models. The other two thresholds depend on the choices within the decision making process (in a similar way as for the weighting factors). In the numerical case every objective is treated the same in which the thresholds per objective are defined as percentages (respectively 2%, 10% and 95%) of the interval between the upper and lower bound of that particular objective.

Table 6.3 Overview monetary values (Maibach et al., 2008)

Objective	**Monetary value** θ_i^M
Efficiency	11 €/hour As an average of different purposes
Air quality	NO_x 6,600 €/ton While the emissions are already weighted within the objective function depended on level of urbanization, the monetary values are used for non-urban areas. Note that also other substances like PM_{10} are of importance when monetizing air quality effects, which are not taken into account here.
Climate	25 €/ton Central value for 2010
Traffic safety	19,000 €/slightly injured 236,600 €/severely injured 1,620,000 €/fatality 82,273 €/injury accident Monetary value of severely injured (direct and indirect economic cost inclusive) in the Netherlands taken as an average. Because the number of injury accidents is calculated, the average ratios (Jansen, 2005) are used to determine slightly injured (1.23), severely injured (0.2341) and fatalities (0.00217).
Noise	$z_3^{mon} = 5.42 z_3^2 - 452.53 z_3 + 9444.7$ The monetary value within the handbook is expressed in per person exposed per year and depends on the Lden dB(A) level that is exceeded. Because the weighted average Sound Power Level is used as the objective in which the Sound Power Level at the source is lowered depending on average distance to the façade and the optimization focuses on a rush hour, the assumption is made that the total number of inhabitants of Almelo (72,500) is exposed to this weighted average Sound Power Level and the monetary value is multiplied by the ratio of simulation time period and hours in a year. A quadratic polynomial was fitted, which directly presents the monetized effects of the weighted average Sound Power Level

Application of CBA

Because the Pareto optimal set is available, it is possible to investigate the consequences of using the CBA to rank the strategies for deploying DTM measures to optimize the formulated objectives. Formulating the MO NDP as a single objective optimization problem from the start, would not have resulted in being able to provide such information for the decision making process. The results show that the strategies that minimize total travel time prevail. Even if a possible error of 10% in the monetary values is introduced, the same solution turns out to be the best in all cases. This is illustrated in figure 6.13, in which the Pareto optimal set is shown after monetizing the different objectives. A slight decrease of noise costs, which is not even visible in the second figure, in which the axis are scaled on a more equal level, results in a major increase in travel time costs and are therefore by far the most dominant. Although the monetary values used within this study are often used within CBA, incorporating externalities as objectives for optimization of DTM-measures in this way, will not result in choosing solutions in which an increase in travel times is accepted, while reducing externalities. Only the externalities that are aligned with efficiency will profit to some extent of minimizing the monetized costs.

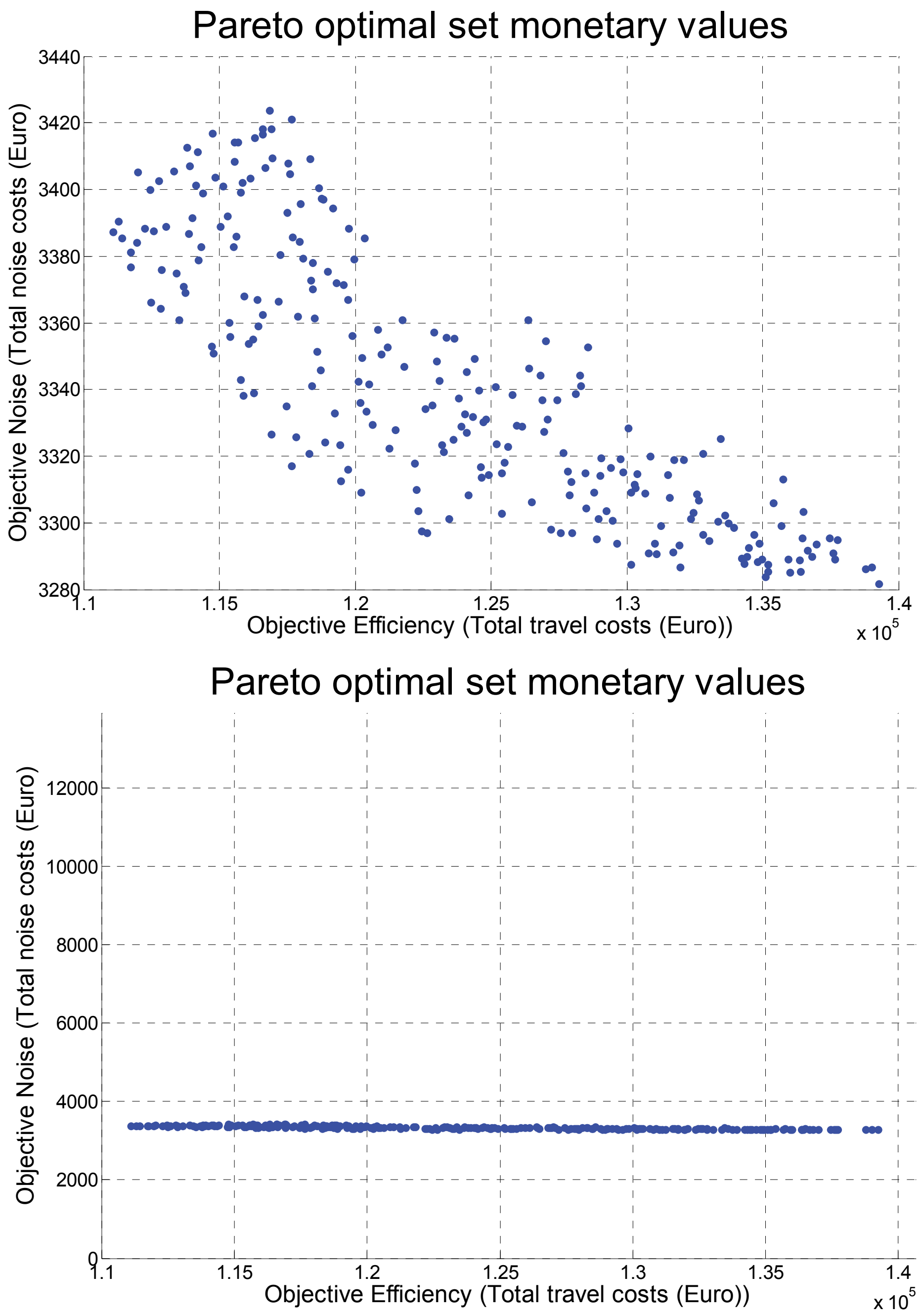

Figure 6.13 Pareto optimal sets in which externalities are monetized

Monetizing the effects will therefore not help in reducing externalities. However, if the decision makers decide that economic trade-off should be the way to rank the solutions, it can be stated that optimizing efficiency will result in the best compromise solution for externalities as well. However, as indicated, the monetary values often used are debatable. Therefore, monetary values are determined for which the trade-offs between the objectives are equal on average with travel time costs (see Table 6.4). This results in monetary values for most externalities that should be much larger (more than 20 times larger) to be equally weighted with travel time costs. Note that these values are related to the average trade-offs.

Table 6.4 Correction factor monetary values if equally weighted with travel time costs

	Air quality	Climate	Traffic safety	Noise*
Monetary values	6,600 €/ton	25 €/ton	82,273 €/accident	3,341 €
Values if equally weighted	694,796 €/ton	4,414 €/ton	1,625,341 €/accident	71,691 €
Factor	105	177	20	21

* Based on average Sound Power Level

Application other ranking methods

Monetizing the effects will not result in reducing externalities in the deployment of DTM measures. If the monetary values are not reconsidered and decision makers do want to reduce externalities, other ranking methods should be applied to better incorporate policy objectives concerning externalities. However, all presented ranking methods still need a compensation principle, which determines how the trade-offs are weighted. Setting these weighting factors is part of the decision making process. By determination of the Pareto optimal set in advance, information is available that can be used to choose appropriate weighting factors. This can be done by using the analysis of the reduced Pareto optimal set and by investigating the sensitivity for these weighting factors and therefore the consequences of setting these factors.

The various ranking methods that are available can result in a different prevalent solution, even though the weighting factors are the same. The main difference between the WSM, WPM and AHP is the way the objectives are normalized, which obviously influences the outcome and level of sensitivity for weighting factors. If the weighting factors are set equally, the objectives are opposed and the shape of the Pareto optimal frontier is convex, the WSM method will rank the solutions high that score average on the individual objectives, even though the relative differences between solutions for an objective are small. The WPM and AHP method are sensitive for relative differences on the outcome between solutions, which means that objectives in which the interval between the upper bound and lower bound is large will dominate the ranking procedure. This means for example that the ranking in these methods can be different using total travel time instead of total vehicle loss hours for efficiency. The WSM (CBA inclusive), WPM and AHP method assumes the outcome of the solutions on the various objectives to be exact.

The WAR and ELECTRE III are two methods that rely less on the exact outcome of the solutions on the various objectives. The ELECTRE III is a fuzzy approach using certain thresholds for indifference, preference and veto and the WAR method only uses the ranking of the solutions on the various objectives. Therefore, the WAR and ELECTRE III method are the only methods presented here that can also rank solutions not part of the convex hull (illustrated in figure 6.14) as the best compromise solution. Using these methods reduces the chance of neglecting interesting solutions that would not be considered using the WSM, WPM or AHP method in a strict way. Therefore, this is also a plea for considering a number of best ranked solutions in the decision making process if WSM, WPM or AHP is used. The ELECTRE III and WAR method offer the possibility to take uncertainties concerning the exact outcome of the objective values into account (i.e. not necessarily interpret the outcome on a ratio scale). However, the WAR method does assume a more or less equal spread of solutions or assumes that the outcomes on the objectives are only suitable to rank per objective. If the difference on that objective is insignificant with respect to the modeling accuracy (i.e. solutions score nearly the same) the method does rank them differently.

Therefore, it is a coarse ranking method, which does no justice to the calculation methods used. Finally, this method is less suitable for bi-objective optimization problems (e.g. if the weighting factors are equal, also all solutions are ranked equally). The ELECTRE III method corresponds best with uncertainties related to the decision making process (e.g. difficulties in setting exact weights) and can take the uncertainties related to the exact outcome of the different solutions into account. Therefore, it is possibly the best method to choose a single best compromise solution. In the ELECTRE III method the indifference thresholds relate to the uncertainties and the preference and veto thresholds to the ability of decision makers to determine if a solution outperforms another. However, this method is more complex and it is less easy to explain the final ranking based on this method. Because transparency can be an important reason for choosing a ranking method to support decision making, the WSM or AHP methods are possibly more interesting for an interactive decision support tool when these are used to select the best compromise solutions to investigate further.

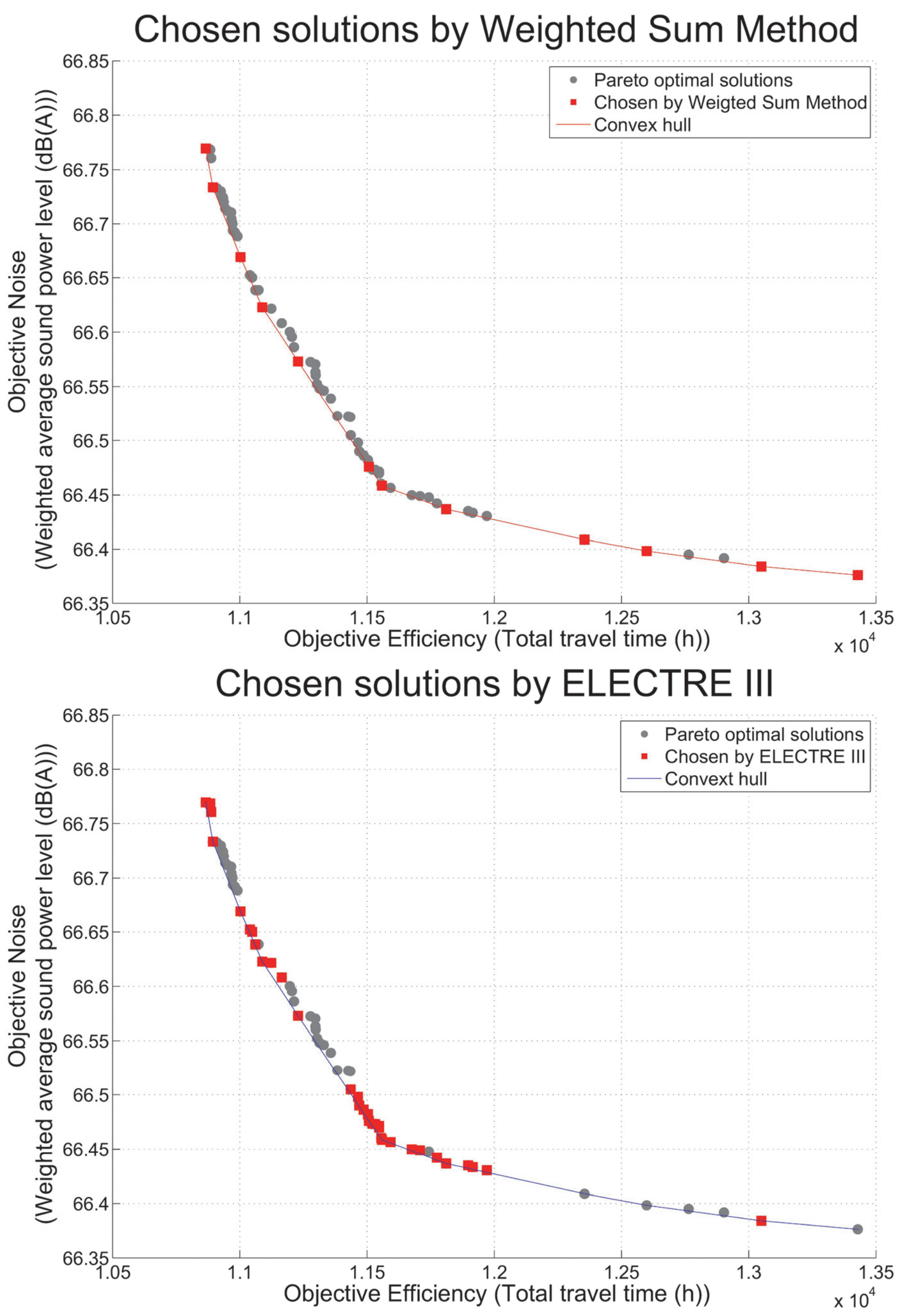

Figure 6.14 Possible outcomes WSM and ELECTRE III for various weighting factors

6.4.4 Conclusions

Ranking methods can be used to select the best compromise solutions that should be investigated further. Application of the often used CBA method shows that the strategies that minimize total travel time prevail. Travel times turn out to be the most dominant objective, which means that only objectives that are aligned with efficiency will profit to some extent when this method is used. If the decision makers decide that economic trade-off should be the way to rank the solutions, it can be stated that optimizing efficiency will result in the best compromise solution for externalities as well. However, as indicated, the monetary values often used are debatable and if decision makers want to take externalities into account more seriously, other ranking methods should be considered. There are many ranking methods available, which result in different rankings, even when the same weighting factors are used. All these methods basically try to rank the solutions by comparing the performance of these solutions on the individual objectives. The main difference between the WSM, WPM and AHP ranking methods is the way the objectives are normalized, which obviously influences the outcomes and sensitivity levels for weighting factors. WAR is a coarse ranking method, which does no justice to the quality of the outcomes. The ELECTRE III is a method that, in contrast to the WSM, WPM and AHP, can take uncertainties into account and is possibly a more suitable method to choose a single best compromise solution. However, this method is complex and therefore not transparent. The WSM or AHP methods are therefore possibly more suitable to use in an interactive decision support tool to select the best compromise solutions to investigate further.

6.5 Concluding remarks

Solving the MO NDP results in a Pareto optimal set, providing valuable information for the decision making process that can be used in an interactive decision support tool to learn about the problem at hand and solutions possible, before deciding how to weigh the various objectives. However, the Pareto optimal set of solutions can become large, especially if the objectives are mainly opposed. As a consequence, the Pareto optimal set may become difficult to analyze and to comprehend. After presenting a possible framework for an interactive decision support tool and explaining what information can be derived from the Pareto optimal set, various pruning and ranking methods are described and applied to illustrate the possible advantages and disadvantages. Reducing the Pareto optimal set using pruning methods and ranking helps to analyze the set and therefore to assist the decision maker. The underlying assumption in the pruning methods, but implicitly also within the solution method to solve the MO NDP, is that there is a correlation between the distances between the solutions in the objective space and the solution space. However, as shown it is possibly true that two distinct solutions in the solution space can result in similar performance in the objective space. This knowledge is of interest, because other aspects (e.g. social support), which are not taken into account in the optimization process as an objective, can be addressed choosing the best compromise solution. If for example there are two solutions that result in similar performance in the objective space, but are distinct in terms of equity (i.e. the differences to what extent certain traffic flows are metered) or complexity (i.e. variation of settings measures over time), the decision maker can use this information to choose the best solution. In Chapter 7 these issues will be further discussed.

By pruning the Pareto optimal set, it is possible to provide a comprehensive analysis of the main choices for the decision makers. Although pruning reduces the Pareto optimal set, still a single compromise solution or set of compromise solutions has to be chosen for further investigation. To be able to rank the solutions a compensation principle is needed. Analysis of the (pruned) Pareto optimal set provides insight in the actual possibilities and can also be used to choose suitable weighting factors. The elementary methods like WSM assume that decision makers are capable of setting these weighting factors precise and assume the outcome of the outcome of the solutions on the various objectives to be exact. Because this will often not true, other methods like fuzzy approaches correspond better with the underlying decision making process and are in accordance with the data quality, but are unfortunately less transparent. For all methods the best ranked solutions should be selected as the best compromise solutions for closer investigation. Based on additional aspects like the mentioned equity or complexity the final decision should be made. This further evaluation can also be extended by incorporating reliability, to cope with day to day variability, robustness, to cope with unexpected situations (e.g. incidents) and sensitivity for certain DTM measures.

Chapter 7

Case studies

Je moet schieten anders kun je niet scoren
You have to shoot, otherwise you can not score
Johan Cruijff

In the previous chapters, the framework and solution approaches are presented, as well as the valuable information contained by the resulting Pareto optimal set and ways to use this information to support decision making. In this chapter the MO NDP is solved for two cases and the results are further analyzed to determine how the objectives are related, what the optimal designs per objective are, what the trade-offs are and what kind of strategies can be used. These cases provide insights on how to deploy DTM measures to optimize externalities on network level.

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Wismans, L.J.J., E.C. Van Berkum and M.C.J. Bliemer (2011). Dynamic Traffic Management Measures to Optimize Air Quality, Climate, Noise, Traffic Safety and Congestion: Effects of a Single Objective Optimization. Bookchapter (ed. J.A.EE. van Nunen, P. Huijbregts and P. Rietveld) *Transitions towards sustainable mobility*, Chapter 16, Part 4, pp. 297-313, DOI: 10.1007/978-3-642-21192-8_16 (ISBN 978-3-642-21191-1, e-ISBN 978-3-642-21192-8), Springer, Heidelberg, Dordrecht London New York.

Wismans, L. J. J., Berkum, E. C. van & Bliemer, M. C. J. (2010). Wisselwerking tussen bereikbaarheid en externe effecten bij de optimalisatie van DVM maatregelen in verkeersnetwerken [Interaction between accessibility and external effects when optimizing DTM measures on network level]. *Tijdschrift Vervoerswetenschap*, (ISSN 0040-7623), 46(2), 44-54.

Wismans, L. J. J., E.C. van Berkum & M. C. J. Bliemer (2012). Effects of optimizing externalities using cooperating DTM measures on network level. *Journal of ITS*, accepted author version posted online: 01 Aug 2012, DOI:10.1080/15472450.2012.716639.

7.1 Introduction

In the previous chapters test cases are used to test and compare various solution approaches and methods to prune and rank the solutions. In this chapter the focus is on the actual outcomes of an optimization. The first case comprises a synthetic network in which first a bi-objective case is used to explain the results. Then for this network the complexity is further increased by considering more objectives. Additionally, the differences between using the RMV method versus the AR-INTERIM-CM model for noise are addressed, because in most cases presented in this research the RMV method is used, which does not reckon with an increase in sound emissions in saturated traffic conditions as a result of increased propulsion noise. The second case is an application of the presented framework for a realistic network of the city of Almelo. For this network the results are analyzed in more detail also for parts of the network, addressing most of the issues discussed in Chapter 6.

7.2 Case 1: Synthetic network

7.2.1 Description

For providing a clear demonstration of the outcomes of an optimization, a simple transport network is hypothesized, consisting of a single origin-destination relation with three alternative routes (see Figure 7.1). One route runs straight through a city with urban roads; the second route is via a ring road using a rural road; the third route is an outer ring road via a highway. Within the network, there are three measures available, two traffic lights and a VMS used to change speed limits (VSL). The highway route is the fastest route based on free flow traffic conditions. However, as a result of travel demand and a lane drop this route becomes congested, which results in traffic using the other routes as well. The available DTM measures can be used to influence traffic conditions and therefore the objectives formulated in Chapter 4 in which also the possible parameter settings of the DTM measures are presented. Although the network is small, it incorporates important elements also found in real networks like urban and non-urban routes when using DTM measures to optimize the externalities.

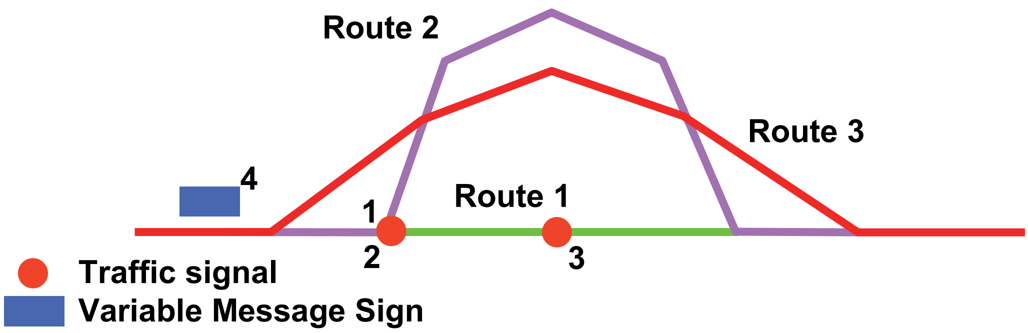


Figure 7.1 Network case 1, synthetic network

In Table 7.1 the solution approaches and parameter settings are presented that are used for the bi-objective, tri-objective and quint-objective case. The parameters are the initial mutation probability ρ_{mut}^{init}, archive size W_u and number of generations H. The parameter settings were chosen based on the results of the comparison of the NSGAII, SPEA2 and SPEA2+ reported in Chapter 5. The initial mutation decreased every generation with 5% for the first 10 generations for all cases. In all cases the solution approaches are converged based on the changes in the S-metric. However, reaching convergence does not mean that the optimization process also results in finding the actual Pareto optimal solutions. Thus the set of solutions is an estimate of the Pareto optimal set. In addition, the solution approach is focused on finding a subset of the Pareto optimal set with a maximum size of the archive size with an even spread along the efficient frontier. As will shown in the next sections, the optimal solutions can be slightly different in the bi-, tri- or quint-objective case. This is possible because heuristics are used and because the solution approaches are stochastic in nature.

Table 7.1 Solution approaches and parameter settings

Case	Objectives	Solution approach	Parameters
Bi-objective	Efficiency Noise	SPEA2+	$\rho_{mut}^{init} = 0.2$ $W_u = 100$ $H = 50$
Tri-objective	Efficiency Climate Noise	NSGAII	$\rho_{mut}^{init} = 0.05$ $W_u = 100$ $H = 100$
	Efficiency Air quality (NO_x) Noise	NSGAII	$\rho_{mut}^{init} = 0.05$ $W_u = 100$ $H = 100$
Quint- objective	Efficiency Air quality (NO_x) Climate Noise Traffic Safety	NSGAII	$\rho_{mut}^{init} = 0.05$ $W_u = 100$ $H = 100$

7.2.2 Bi-objective case

For the bi-objective case the objectives efficiency and noise are optimized. The results of the optimization are presented in Figure 7.2 showing the dominated and non-dominated solutions based on all assessed solutions by the solution approach. In total the algorithm found 300 Pareto optimal solutions analyzing all 5,100 assessed solutions, while the algorithm itself delivers 100 Pareto optimal solutions after the last generation (i.e. size of archive).

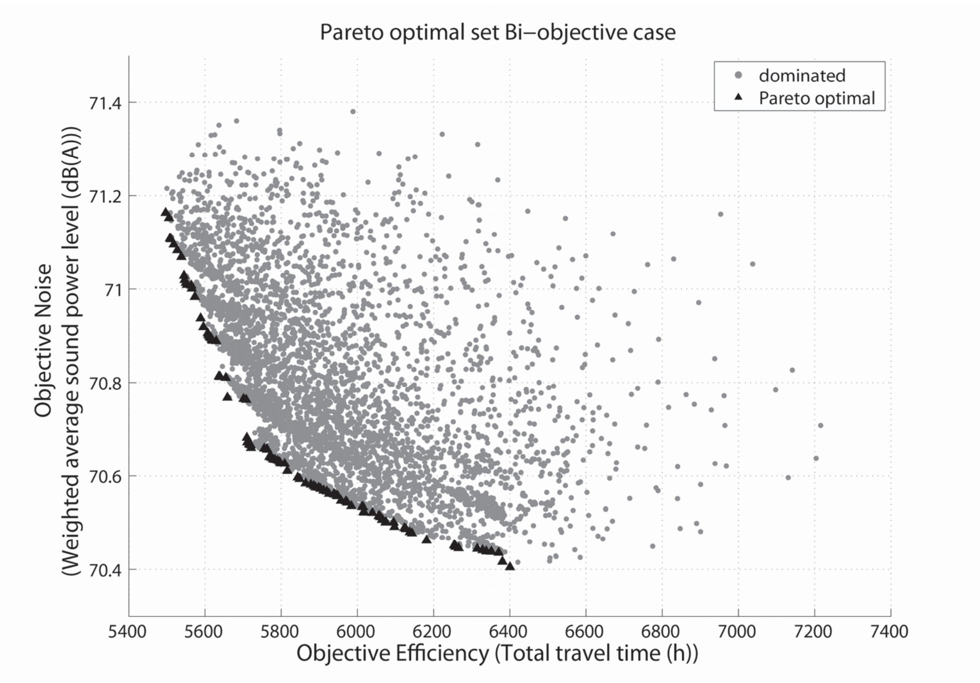


Figure 7.2 Pareto optimal solutions (efficiency and noise)

The Pareto optimal set (non-dominated solutions) shows that these two objectives are opposed. The optimal solution for efficiency is one of the worst solutions for noise and vice versa. Figure 7.2 also shows that there are gaps in the efficient frontier. Closer investigation of the Pareto optimal set shows that most of these are a result of the VSL measure and its discretization. This is clearly illustrated in Figure 7.3 in which the Pareto optimal solutions are clustered based on the combination of the settings of the VSL over time.

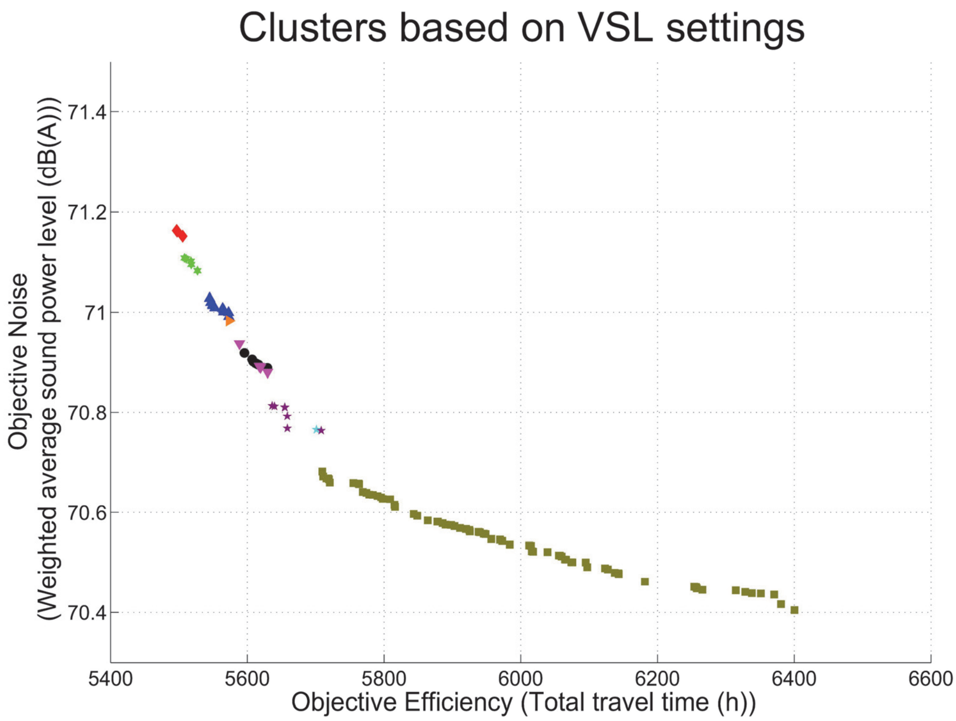


Figure 7.3 Clustering Pareto optimal solutions based on VSL settings

The optimal designs for noise uses the lowest value for the speed limit on the highway (80 km/h) and meters traffic using the traffic signals, while the optimal design for efficiency uses mainly a speed limit of 100 km/h and high capacities at the traffic signals. Note that in case 1 it is assumed that capacity increases when lowering the speed limit. Total travel time is 16.4% higher for the optimal design for noise versus the optimal design for efficiency. The average sound power level for the optimal design for efficiency is 1.1% higher than for noise. Note that sound power level is expressed on a logarithmic scale. Using sound energy, the optimal design for efficiency produces 19.1% more energy than the optimal design for noise. Given the optimal designs, optimizing efficiency aims at avoiding congestion using full capacity of the available routes, while optimizing noise aims at lowering the driving speeds as much as possible and avoiding traffic using the urban routes. However, this does not mean that all traffic signal should be given full capacity to optimize efficiency. Assessing the solution in which all traffic signals are given full capacity and the settings for the VSL are based on the found optimal design for efficiency (i.e. 100 km/h for all time periods) results in 17.6% higher travel times. The reason why this solution performs even worse than the optimal design for noise on efficiency, is due to the fact that route 1 through the city is the fastest alternative for the saturated highway. As a result queues are formed upstream of traffic signal 2 blocking traffic (trying to use or) using route 3. As a result route three is little used. The optimal design for efficiency therefore reduces capacity at traffic signal 3, resulting in a more equal spread of traffic using all three routes avoiding congestion.

Using the Pareto optimal solutions the trade-offs can be determined. In Figure 7.4 the trade-offs between the points forming the convex hull are shown in which these are sorted based on the outcome of one objective. In this case the trade-off represents the decrease in total travel time, accepting an increase of the weighted average sound power level with 1 dB(A). The slope of the lines connecting these points represent the trade-offs.

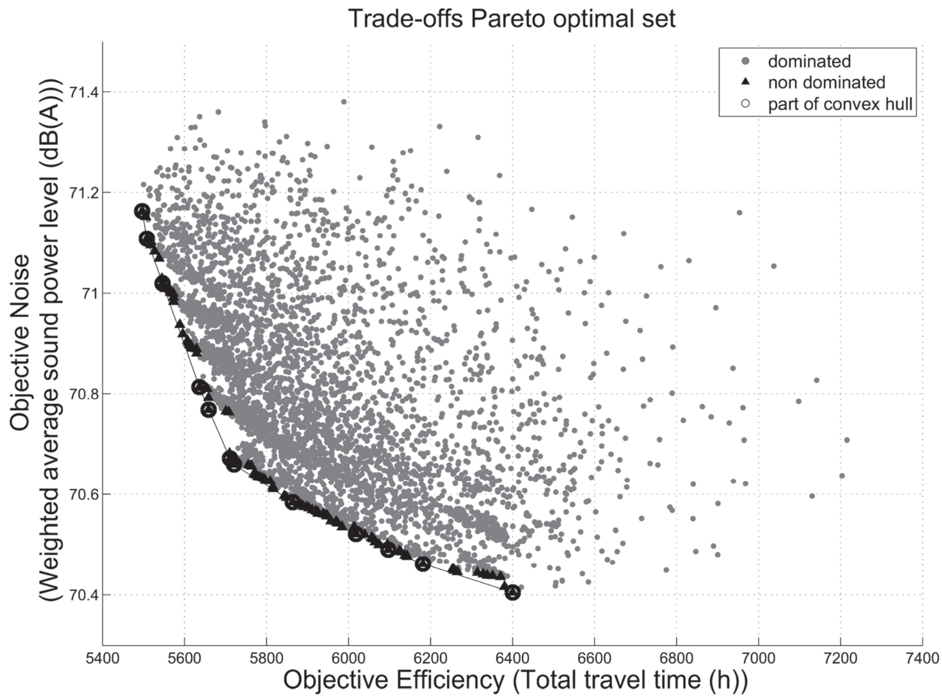


Figure 7.4 Trade-offs Pareto optimal set

Table 7.2 presents the trade-offs in terms of increase in travel time to reduce the average sound power level with 1 dB(A) between the points forming the convex hull (sorted on outcome efficiency).

Table 7.2 Trade-offs

From	To	Trade-offs
Optimal design efficiency	2	-207.20
2	3	-431.72
3	4	-436.28
4	5	-490.79
5	6	-546.41
6	7	-806.64
7	8	-1885.78
8	9	-2470.12
9	10	-2545.88
10	11	-2921.79
11	Optimal design noise	-3828.20
Average		-1191.22

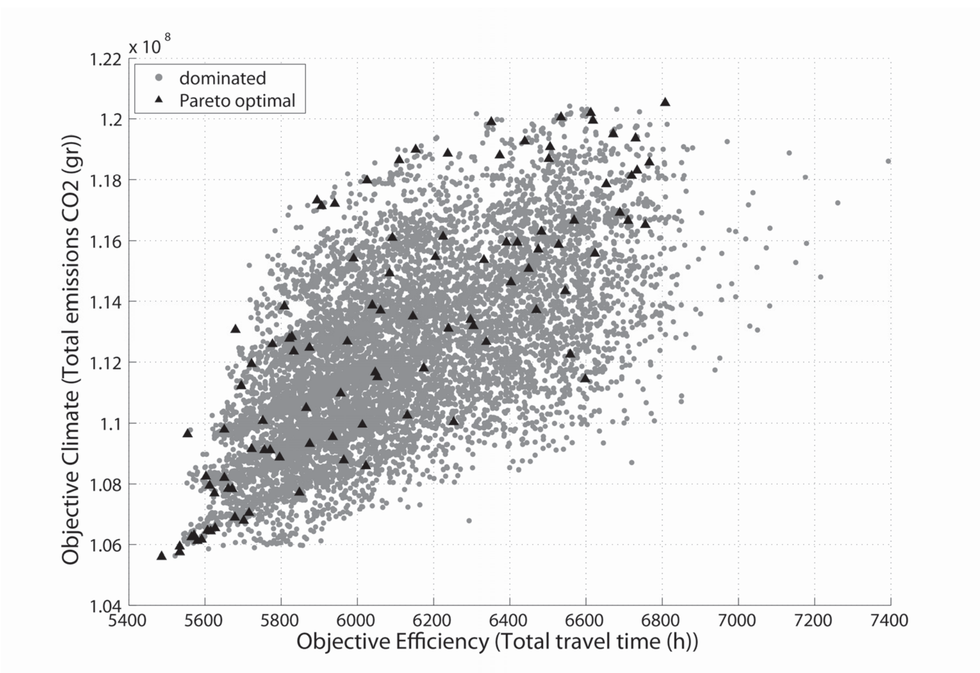
Note that in this case it is not actually possible to reduce 1dB(A), while the points itself determine the increase and decrease possible and therefore the step size possible. The average trade-off represents the weights needed to weigh the two objectives equally given the optimal designs per objective using the absolute values of the objectives. Based on the trade-offs, it is possible to determine how the objectives should be weighted (assuming linear weights) to end up in a certain design, but also the sensitivity for the weightings. For example, if noise is weighted between 436.28 and 490.79 times more than efficiency, the best compromise solution would be solution 4 or if noise is weighted 2470.12 times more than efficiency, solution 8 as well as solution 9 would be the best compromise solutions (see Table 7.2). The trade-offs can also be used in a different way, using a specific solution as a starting point discussing if a certain trade-off is accepted taking into account the possible step size. In that case the trade-offs between all points (in this case 66 possible combinations) become relevant.

7.2.3 Tri-objective case

In the tri-objective cases an additional objective is considered next to efficiency and noise. In the first tri-objective case the objective climate (measured by total CO_2 emissions) is added and in the second case the objective air quality (measured by weighted NO_x emissions). Although both emissions, CO_2 and NO_x, show a similar relation with speed (i.e. higher emissions in saturated traffic conditions and for highways with a speed limit of 120 km/h, higher emissions in free flow conditions), there is a difference. For the objective climate the location where CO_2 is emitted is irrelevant, while for NO_x, emissions in urbanized areas should be avoided. This is taken into account using a weighted sum of NO_x emissions in which the weights depend of urbanization. Based on this knowledge and the results of the bi-objective case, it can be expected that the objective climate should be more aligned with efficiency than air quality.

Efficiency, climate and noise

In the first tri-objective case, the objective climate is considered as well. Figure 7.5 shows the results in two dimensions. Note that the Pareto optimal solutions are shown based on all three objectives. After analyzing all 10,100 assessed solutions (by the solution approach), it turns out that 1,015 solutions are Pareto optimal. For the analysis and presented in Figure 7.5 the 100 solutions presented by the solution approach after the last generation are used.



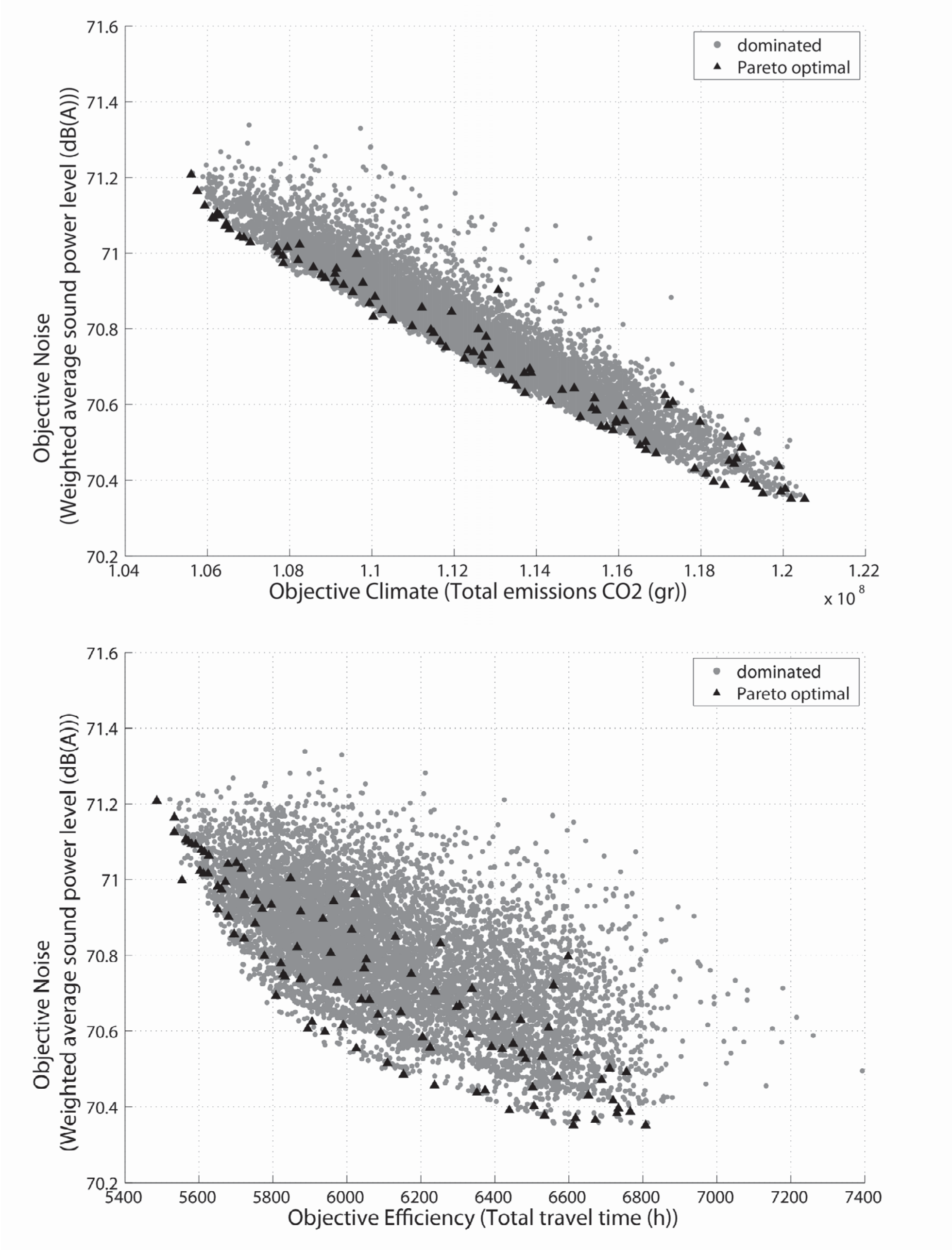


Figure 7.5 Pareto optimal solutions (efficiency, climate and noise)

The results show that in this case the objectives efficiency and climate are strongly aligned, because there is even one single solution that optimizes both objectives. One reason for this outcome is the fact that emissions are high in case of saturated traffic conditions and when the speeds on highways are high. Because the optimal design for efficiency deploys the VSL with a lower speed limit on the highways (see Section 7.2.2), both objectives are aiming for similar traffic conditions. Optimizing efficiency aims at avoiding congestion using full capacity of the available routes, which is in this case also good for minimizing CO_2 emissions. However, both objectives, efficiency and climate, are opposed to the objective noise. Optimizing noise aims at lowering the driving speeds as much as possible and also avoiding traffic using the urban routes.

The performance of the optimal designs per objective is presented in Table 7.3 by scoring their performance relative to the outcome of the optimal designs of the other objectives. Each column represents the outcome of the optimal design of that specific objective on the other objectives. In mathematical form:

$$Index\left(j_i\right) = \frac{z_i(S_j^*)}{z_i(S_i^*)} \times 100 \text{ , with } S_i^* = \arg\min_S z_i \text{ and } S_j^* = \arg\min_S z_j \qquad [7.1]$$

This means that in this optimization the optimal design for noise results in 24.1% higher travel times en 14.1% higher CO_2 emissions than the optimal design for efficiency (equal to optimal design for climate).

Table 7.3 Performance optimal designs

	Optimal design for objective		
	Efficiency	**Climate**	**Noise**
Efficiency	**100.0**	100.0	124.1
Climate	100.0	**100.0**	114.1
Noise	101.2	101.2	**100.0**

Analyzing the trade-offs in the tri-objective case becomes in general more complex in a sense that there exist trade-offs between all Pareto optimal points part of the convex hull (in this case 24 solutions out of the 100 Pareto optimal solutions) and the slopes representing the weights are in this case (three-dimensional objective space) planes formed by at least three solutions (in this case 33 planes), shown in Figure 7.6.

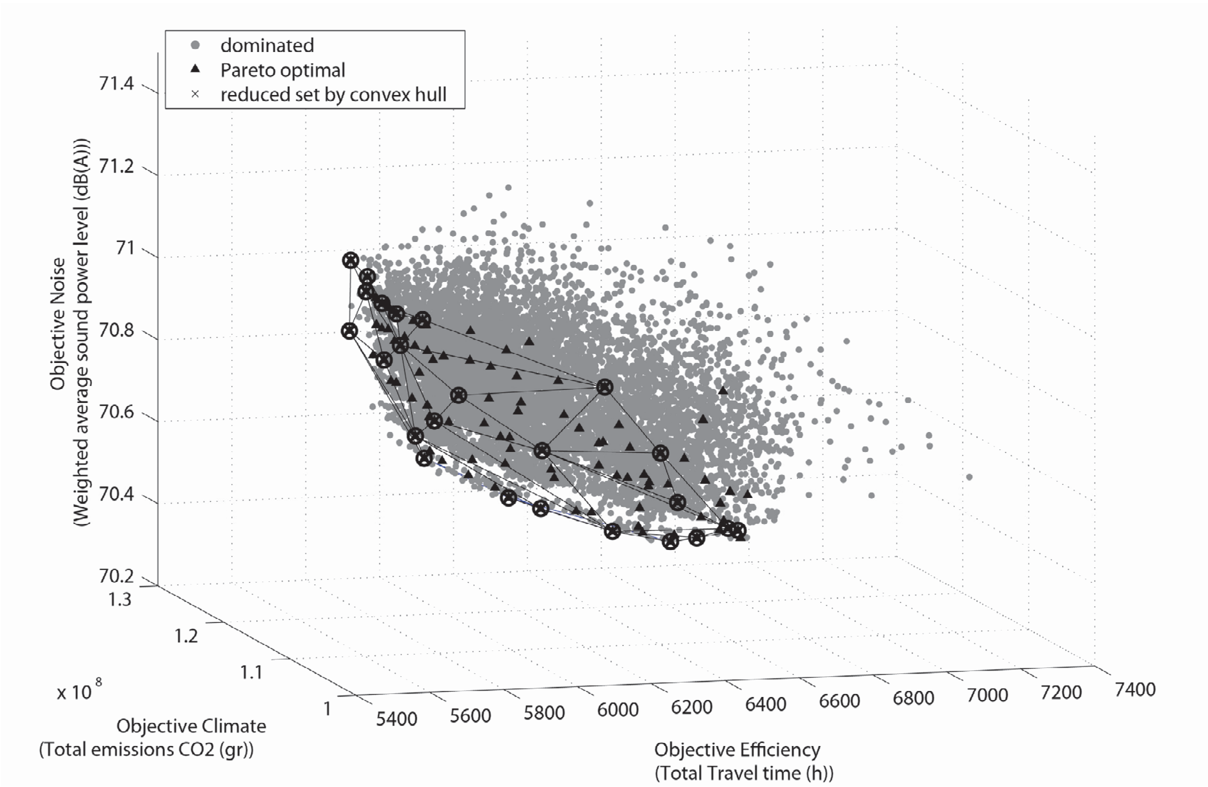


Figure 7.6 Convex hull

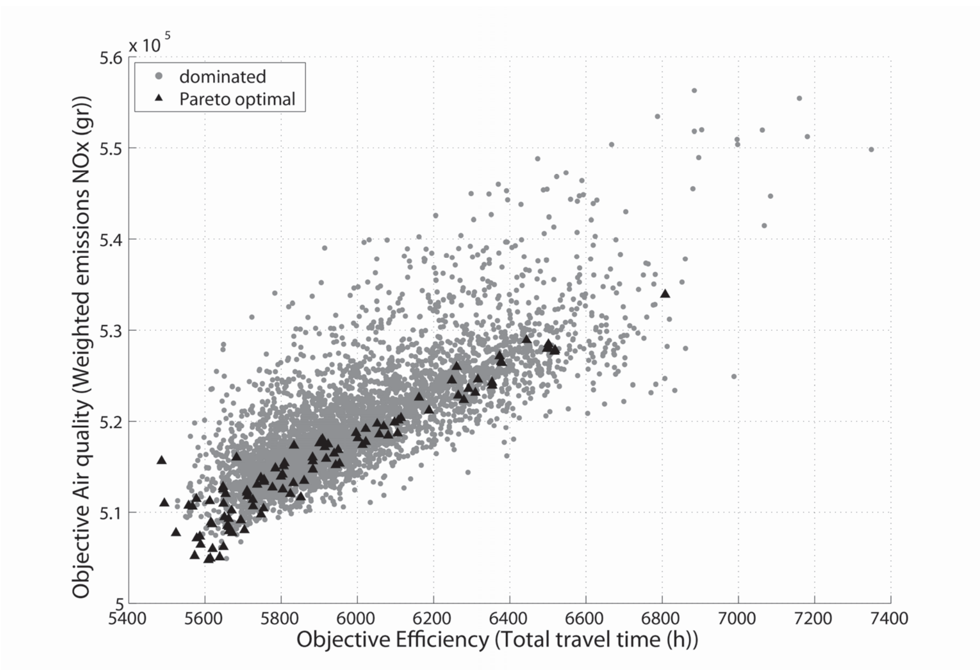
Because there are many trade-offs and in this case in three dimensions (e.g. increase in travel time and increase of CO_2 emissions to reduce the average sound power level with 1 dB(A)) resulting in 276 possible combinations, only the average trade-offs are presented in Table 7.4 based on the optimal designs per objective. The average trade-offs represent the weighting factors needed to weigh the two objectives equally given the optimal designs. The bold printed figures are the average trade-offs between the performances of the optimal designs, while the other figures in the same column represent the effect on the other objectives as well. This means for example that the average trade-off between efficiency and noise is -6.48×10^{-4}, meaning that accepting an increase of total travel time with 1 hour results on average in a decrease of 6.48×10^{-4} dB(A), but also in an increase of 1.13×10^{4} grams of CO_2. Note that the effect on the other objective (in this case climate) is related to the level in which the different objectives are aligned or opposed as presented in Figure 7.5 and that the trade-offs are bounded. In this case the optimal design for climate is equal to the optimal design for efficiency, which means that no average trade-off can be determined for these two objectives. Further note that the average trade-off between the optimal design for noise and efficiency (-1.54×10^{3}) is the inverse of the average trade-off between efficiency and noise (-6.48×10^{-4}).

Table 7.4 Average trade-offs

	Efficiency (1 hour)		**Climate (1 gram)**		**Noise (1 dB(A))**	
	Climate	**noise**	**Efficiency**	**Noise**	**Efficiency**	**Climate**
Efficiency			-	8.86E-05	**-1.54E+03**	-1.54E+03
Climate	-	1.13E+04			-1.74E+07	**-1.74E+07**
Noise	-	**-6.48E-04**	-	**-5.74E-08**		

Efficiency, air quality and noise

In the second tri-objective case, air quality is added instead of climate. Figure 7.7 shows the results in two dimensions (for the combination efficiency - air quality and air quality – noise). Note that the Pareto optimal solutions are shown based on all three objectives. For the analysis and presented in Figure 7.7 the 100 solutions presented by the solution approach after the last generation are used.



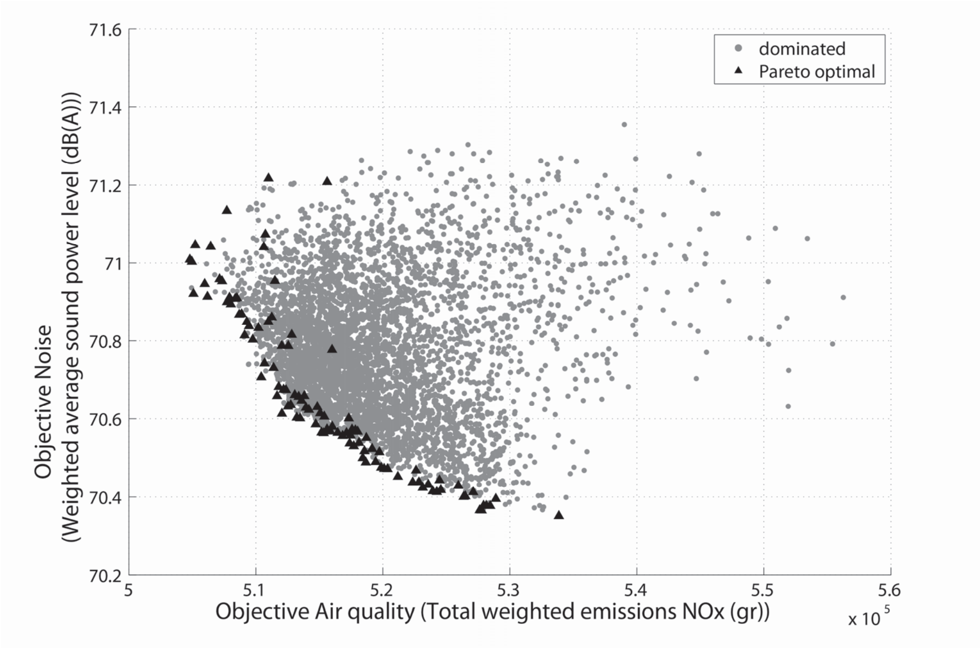


Figure 7.7 Pareto optimal solutions (efficiency, air quality and noise)

The results show that in this case the objectives efficiency and air quality are aligned, but it is not possible to optimize both using one single solution. Because for air quality the total emissions of NO_x is a weighted sum, in which the weights depend on the level of urbanization, the results are different compared with the previous tri-objective case. For climate the location of emissions is not relevant. Therefore, the optimization of air quality aims at avoiding congestion and high speeds and searches for the best trade-off between minimizing traffic using the urban roads and the level of congestion on the highway. As a result the objectives air quality and noise are slightly less opposed than climate and noise, but still opposed objectives.

Although not tested, it can be expected that the objectives air quality and efficiency will be more opposed if higher weights are used for the emissions of NO_x in urban areas depending on the influence of these weights on the trade-off between congestion and use of urban roads. The performance of the optimal designs per objective is presented in Table 7.5 by scoring their performance relative to the outcome of the optimal designs of the other objectives. In this case the optimal design of efficiency results in 2.1% higher weighted NO_x emissions and the optimal design for noise in 5.8% higher NO_x emissions.

Table 7.5 Performance optimal designs

	Optimal design for objective		
	Efficiency	**Air quality**	**Noise**
Efficiency	**100.0**	102.2	124.1
Air quality	102.1	**100.0**	105.8
Noise	101.2	100.9	**100.0**

In this case 29 solutions out of the 100 Pareto optimal solutions are part of the convex hull that form 45 planes and result in 351 possible combinations. The average trade-offs are presented in Table 7.6 based on the optimal design per objective. The bold printed figures are the average trade-offs between the optimal designs, while the other figures in the same column represent the effect on the other objectives as well. This means for example that the average trade-off between efficiency and air quality is -8.80×10^{1}, meaning that accepting an increase of total travel time with 1 hour results on average in a decrease of 88 grams of (weighted) NO_x, but also in a decrease of 1.62×10^{-3} dB(A).

Table 7.6 Average trade-offs

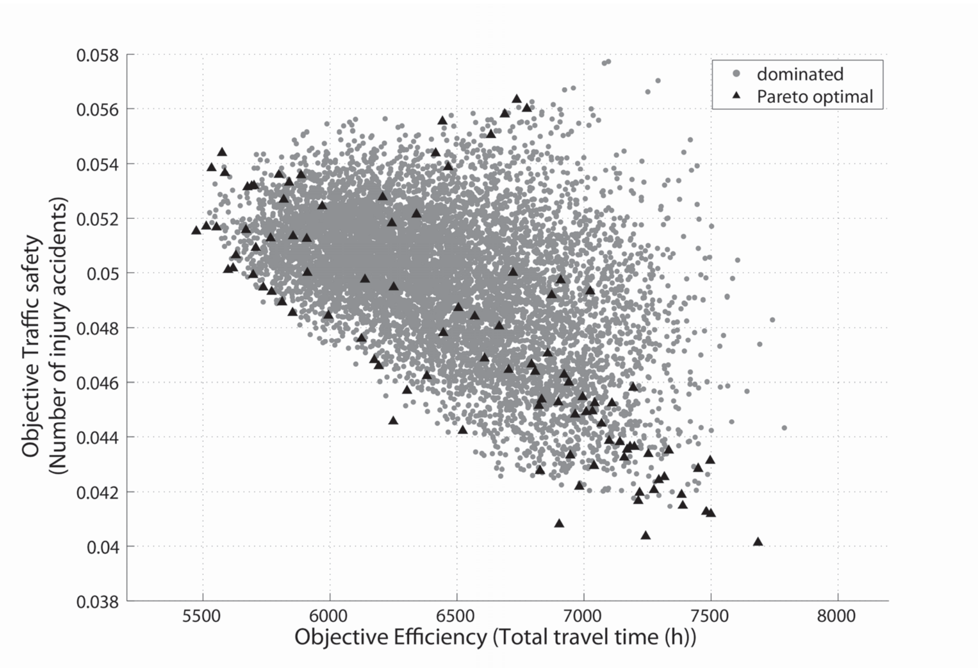
	Efficiency (1 hour)		Air quality (1 gram)		Noise (1 dB(A))	
	Air quality	**noise**	**Efficiency**	**Noise**	**Efficiency**	**Air quality**
Efficiency			**-1.14E-02**	4.13E-02	**-1.54E+03**	-1.82E+03
Air quality	**-8.80E+01**	1.38E+01			-1.74E+07	**-4.42E+04**
Noise	-1.62E-03	**-6.48E-04**	1.84E-05	**-2.26E-05**		

7.2.4 Quint-objective case

In the last case all objectives are considered. This means that the objectives efficiency, air quality, climate, traffic safety and noise are all optimized. In Chapter 4 two methods are presented to assess the effects on noise. The RMV method is used in all cases presented thus far and also used in the last case on the realistic network of the city of Almelo. Because this method does not take into account the increase in sound power level in saturated conditions, the optimal design found for noise particularly aims at lowering speed as much as possible. However, at lower speeds propulsion noise becomes the dominant source of sound emissions and increases because of accelerations, which occurs during saturated traffic conditions. The AR-INTERIM-CM model, does take this effect into account. Therefore this method is used in the second quint-objective case to investigate to what extent this influences the optimal design for noise and therefore the relations with the other objectives.

All objectives (noise based on RMV method)

In the quint-objective case all objectives are considered. Figure 7.8 shows the results in two dimensions for efficiency – traffic safety and noise – traffic safety. Note that the Pareto optimal solutions are shown based on all five objectives. For the analysis and also shown in Figure 7.8 the 100 Pareto optimal solutions presented by the solution approach after the last generation are used.



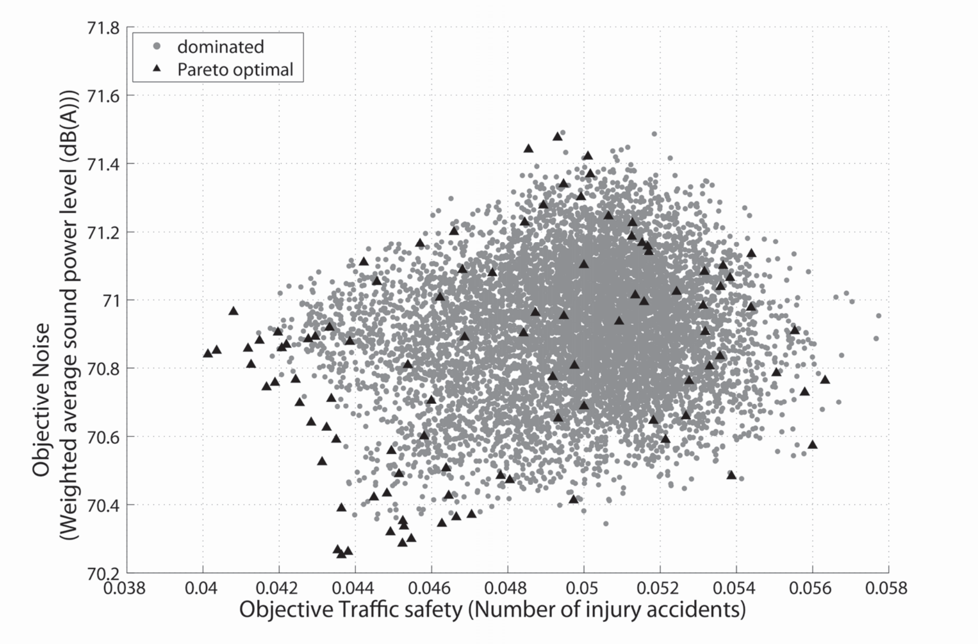


Figure 7.8 Pareto optimal solutions (efficiency, air quality, climate, traffic safety and noise)

Analyzing all assessed solutions by the solution algorithm, shows that it found 1,598 Pareto optimal solutions in total. The results show that traffic safety is opposed to efficiency and the objectives noise and safety are nor opposed nor aligned. For traffic safety the optimal design aims at maximizing the use of the relative safest route using the highway and avoiding the use of the urban route. The optimal design for traffic safety uses the maximum speed limit at the highways (120 km/h) and low capacities for the traffic signals. As a result the highway is used most compared to all other optimal designs. The main difference with the optimal design for noise is that the speed limit at the highway is set the lowest (80 km/h) to reduce noise emissions also for the uncongested parts of the highway. Although not all possible combinations are shown in figures, the other relations can be derived from the ones shown for efficiency (e.g. air quality and climate are aligned with efficiency means that air quality and climate are aligned as well).

Table 7.7 Performance optimal designs

	Optimal design for objective				
	Efficiency	**Air quality**	**Climate**	**Traffic safety**	**Noise**
Efficiency	**100.0**	103.6	101.8	140.4	131.5
Air quality	100.6	**100.0**	100.7	113.3	106.7
Climate	100.1	102.7	**100.0**	112.8	117.3
Traffic safety	128.4	128.5	135.5	**100.0**	108.7
Noise	101.3	101.1	101.3	100.8	**100.0**

The performance of the optimal designs per objective is presented in Table 7.7 by scoring their performance relative to the outcome of the optimal designs of the other objectives. In this case the optimal design of efficiency results in 28.4% higher number of injury accidents and the optimal design for noise in 8.7% higher number of injury accidents. The outcome of this optimization also resulted in finding slightly better solutions for efficiency, climate and noise, a slightly worse optimal design for air quality and not one single optimal solution for climate and efficiency, compared to the earlier presented bi- and tri-objective cases. However, the optimal designs for climate and efficiency are still close to each other. Although the algorithm did converge, it also means that the solution approach has difficulties to find these slightly better optimal designs, because in this case slightly better solutions are found for some objectives. However, slightly better optimal design on a certain objective can result in significant effects on the other objectives, because often in those areas of objective space the trade-offs are large (assuming the efficient frontier being convex). Moreover, it also shows that it is not necessarily true that more objectives means that it is more difficult to find better performing optimal designs. This is possibly true because an additional objective results in a better search in certain areas in solution space, for which otherwise, because of the genetic operators, less children would have been proposed.

Table 7.8 Average trade-offs

	Efficiency (1 hour)			
	Air quality	**Climate**	**Traffic safety**	**Noise**
Air quality	**-1.48E+01**	7.69E+00	2.93E+01	1.81E+01
Climate	1.44E+04	**-8.63E+02**	6.09E+03	1.05E+04
Traffic safety	2.70E-07	2.83E-05	**-5.15E-06**	-4.58E-06
Noise	-8.89E-04	-3.23E-04	-1.48E-04	**-5.30E-04**
	Air quality (1 gram)			
	Efficiency	**Climate**	**Traffic safety**	**Noise**
Efficiency	**-6.77E-02**	-2.57E-02	2.98E-02	4.49E-02
Climate	-9.74E+02	**-7.91E+02**	1.57E+02	4.51E+02
Traffic safety	-1.83E-08	7.68E-07	**-1.69E-07**	-2.33E-07
Noise	6.01E-05	3.84E-05	-2.28E-06	**-2.18E-05**
	Climate (1 gram)			
	Efficiency	**Air quality**	**Traffic safety**	**Noise**
Efficiency	**-1.16E-03**	3.25E-05	1.56E-04	8.89E-05
Air quality	-8.91E-03	**-1.26E-03**	4.73E-03	1.66E-03
Traffic safety	-3.28E-08	-9.71E-10	**-1.05E-09**	-5.89E-10
Noise	3.74E-07	-4.86E-08	-2.18E-08	**-4.83E-08**
	Traffic safety (1 injury accident)			
	Efficiency	**Air quality**	**Climate**	**Noise**
Efficiency	**-1.94E+05**	-1.76E+05	-1.48E+05	-1.39E+05
Air quality	-5.69E+06	**-5.91E+06**	-4.49E+06	-9.61E+06
Climate	-1.18E+09	-9.30E+08	**-9.50E+08**	1.35E+09
Noise	2.88E+01	1.35E+01	2.07E+01	**-1.67E+02**
	Noise (1 dB(A))			
	Efficiency	**Air quality**	**Climate**	**Traffic safety**
Efficiency	**-1.89E+03**	-2.06E+03	-1.84E+03	8.29E+02
Air quality	-3.41E+04	**-4.59E+04**	-3.44E+04	5.74E+04
Climate	-1.99E+07	-2.07E+07	**-2.07E+07**	-8.03E+06
Traffic safety	8.63E-03	1.07E-02	1.22E-02	**-5.97E-03**

In this case 29 solutions out of the 100 Pareto optimal solutions are part of the convex hull resulting in 406 possible combinations. Because objective space has in this case 5 dimensions there are 123 possible combinations of 5 solutions. The average trade-offs are presented in Table 7.8 based on the performance of the optimal design per objective. The bold printed figures are the average trade-offs between the optimal designs, while the other figure in the same column represent the effect on the other objective as well. This means for example the average trade-off between efficiency and air quality is -1.48×10^{1}, meaning that accepting an increase of total travel time with 1 hour results on average in a decrease of 14.8 grams of (weighted) NO_x, but also in an increase of 14,400 grams of CO_2, an increase of injury accidents of 2.70×10^{-7} and a decrease of 8.89×10^{-4} dB(A).

Noise based on RMV method versus AR-INTERIM-CM model

In the second quint-objective case, an other method is used to assess the noise objective. The RMV method only takes into account the increase or decrease of noise emissions as a result of the impact of a DTM strategy on speeds. However, in saturated traffic conditions the propulsion noise increases as a result of accelerations (and decelerations). This is especially of importance when speeds are low, because in that case propulsion noise dominates rolling noise and therefore especially on urban roads. Figure 7.9 presents the results in two dimensions for efficiency and noise. Compared with the optimization in which the RMV method is used, these objectives are in this case less opposed. Using the RMV method the optimal design aims at low speeds, using the lowest speed limit (80 km/h) for the highways and low capacities at the traffic signals. As a result congestion occurs at the highway and in the city as well. Using the AR-INTERIM-CM model the optimal designs also aims at low speeds, while avoiding congestion especially in the urban area. This means that this optimal design also uses the lowest speed limit (80 km/h) on the highway, but capacities at the traffic signals are higher. As a result there is no congestion in the city, but also more traffic using the urban and rural route and less congestion on the highways.

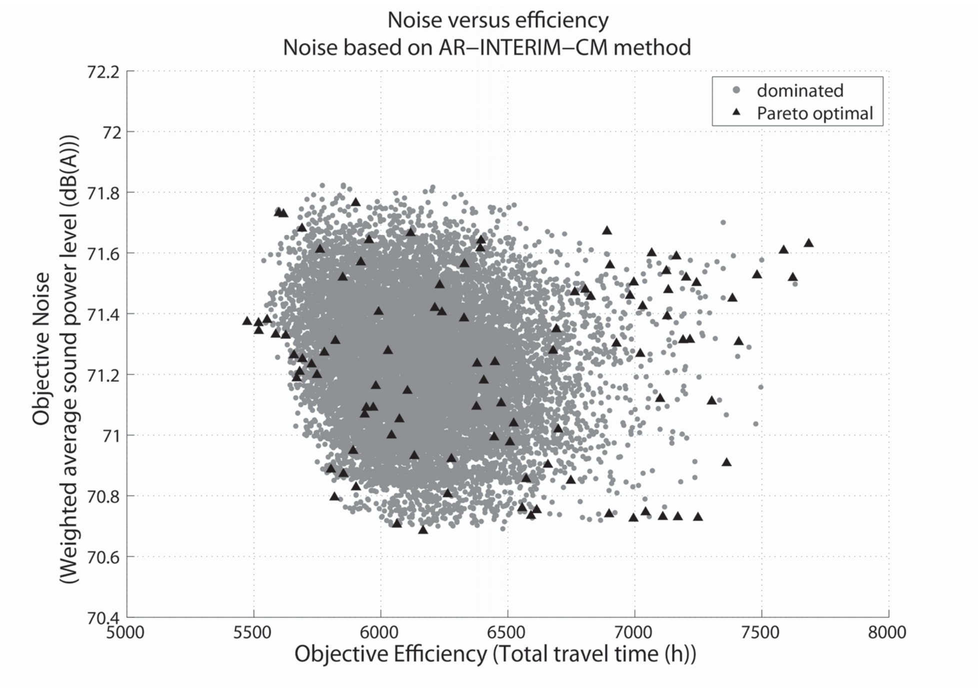


Figure 7.9 Pareto optimal solutions (efficiency and noise based on AR-INTERIM-CM)

Because in this case there is less congestion, the impact of choosing this optimal design at the other objectives is also less. In Table 7.9 the performance of the optimal designs for noise based on RMV and AR-INTERIM-CM are presented, by scoring their performance relative to the outcome of the optimal designs of the other objectives.

Table 7.9 Performance optimal designs

	Optimal design for objective	
	Noise (RMV model)	**Noise (AR-INTERIM-CM model)**
Efficiency	131.5	112.7
Air quality	106.7	102.4
Climate	117.3	112.2
Traffic safety	108.7	129.0

The results show that in objective space the optimal design for noise based on AR-INTERIM-CM is closer to the optimal design for efficiency, air quality and climate. This can be explained by the necessity to avoid congestion, mainly in urban areas, for noise as well. Because more traffic is using the urban and rural roads noise is more opposed to traffic safety.

The average trade-offs also change and are presented in Table 7.10. In this case only the average trade-offs are presented for noise based on the AR-INTERIM-CM model. The bold printed figures are the average trade-offs between the optimal designs, while the other figure in the same column represent the effect on the other objective as well. This means for example the average trade-off between Noise and air quality is -2.40×10^{4}, meaning that accepting an increase of sound power level with 1 (weighted) dB(A) results on average in a decrease of 34 kg of (weighted) NO_x, but also in an decrease of 990 hour total travel time, 19.5 tons of CO_2 and a decrease of injury accidents of 3.39×10^{-4}. Almost all average trade-offs are smaller when the AR-INTERIM-CM model is used, except for traffic safety, which is also expected as explained for the optimal designs.

Table 7.10 Average trade-offs

	Noise (1 dB(A))			
	Efficiency	**Air quality**	**Climate**	**Traffic safety**
Efficiency	**-1.01E+03**	-9.90E+02	-8.84E+02	1.61E+03
Air quality	-1.33E+04	**-2.40E+04**	-1.33E+04	5.89E+04
Climate	-1.84E+07	-1.95E+07	**-1.85E+07**	8.75E+05
Traffic safety	-3.24E-04	-3.39E-04	2.67E-03	**-1.23E-02**

7.2.5 Conclusions

Case 1 is used to show the feasibility of the approach and the outcome of a bi-objective, tri-objective and quint-objective optimization. In addition, the differences between assessing the effects with the AR-INTERIM-CM noise model, taking the effect of increasing propulsion noise in saturated traffic conditions into account, and the RMV model, which is used in most cases in this research. The results show that in this first case the objectives efficiency, air quality and climate are aligned and are opposed to traffic safety and noise. The optimal design for efficiency aims for avoiding congestion, using full capacity of all three available routes. Avoiding congestion is also of importance for the emissions of substances, which in this case means that climate and efficiency are almost co-linear. Because for air quality the emissions in urbanized areas are weighted higher, the optimal design for air quality searches for the best trade-off between avoiding congestion and use of the urban routes. For traffic safety the optimal design tries to maximize the use of the highway route, which is the safest route, and avoiding urban routes. For noise, the optimal design when using the RMV model aims at lowering speeds as much as possible and avoiding traffic using the urban routes. However, when the increase of propulsion noise in saturated traffic conditions is taken into account using the AR-INTERIM-CM noise model, the optimal design for noise still aims at lowering speeds, but avoiding congestion as well. In the latter case noise is therefore less opposed to efficiency than if this effect is not reckoned with.

The optimization in case 1 further showed, that although the algorithms had converged for all optimization, the outcome in terms of optimal designs were slightly different for the bi-objective, tri-objective and quint-objective cases. The solution approach has difficulties to find slightly better optimal designs. However, slightly better optimal design on a certain objective can result in significant effects on the other objectives, because often in those areas of objective space the trade-offs are large. Moreover, in the quint-objective case the algorithm found slightly better optimal designs than in the tri-objective case. This means that although expected, it is not necessarily true that more objectives means that it is more difficult to find better optimal designs. This is possibly the case, because an additional objective can result in a better search in certain areas in solution space. However, in general considering more (opposed) objectives also means that a larger part of the feasible solutions are Pareto optimal solutions. The total number of Pareto optimal solutions found by the solution approach, after analyzing all assessed solutions also increased (bi-objective 6%, tri-objective 10%, quint-objective 16%). Adding objectives will increase the percentage of feasible solutions that are Pareto optimal solutions, which means that at a certain point the added value of the optimization is mainly searching the optimal designs per objective and an equal spread in Pareto optimal solutions.

7.3 Case 2: Almelo

7.3.1 Description

The second case is used to obtain knowledge on the optimization of externalities using DTM measures considering a larger and realistic network of the city of Almelo in the eastern part of the Netherlands. The model contains the major roads and there are 9 DTM measures available as shown in Figure 7.10. The traffic signals are chosen because these are the main entrances to the city and the VMSs, used as VSL, because with this measure traffic using the two entrances via the highway can be influenced. In this case no changes in capacity are assumed as a result of changing the speed limit. The possible parameter settings of the DTM measures are presented in Chapter 4. The radial roads are numbered, because of the analysis presented in this section.

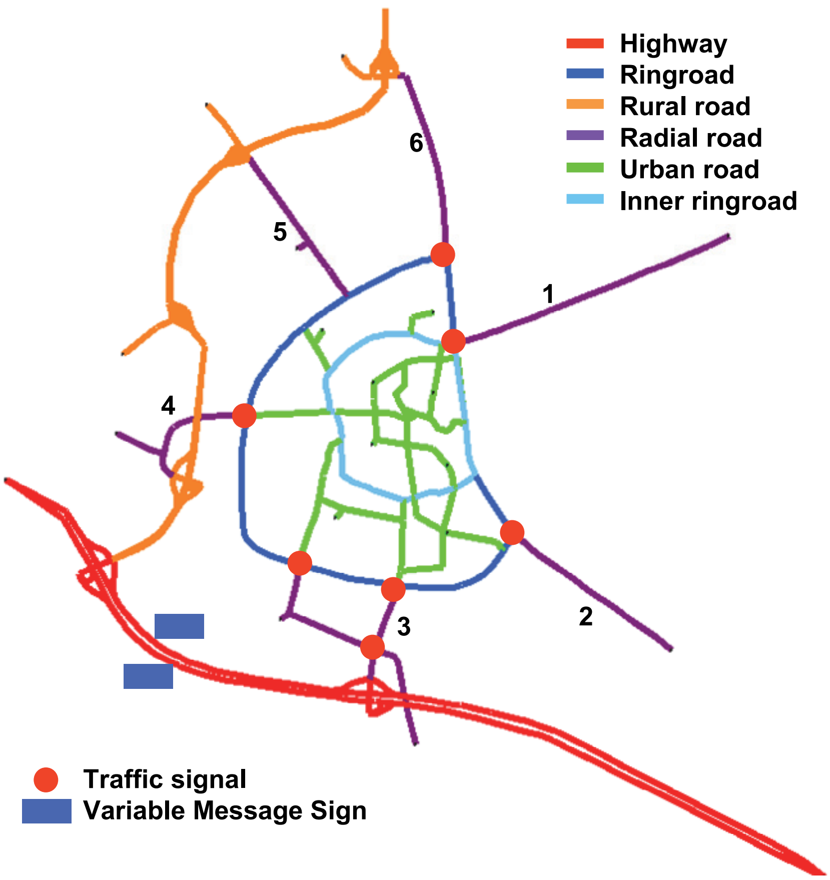


Figure 7.10 Network Almelo

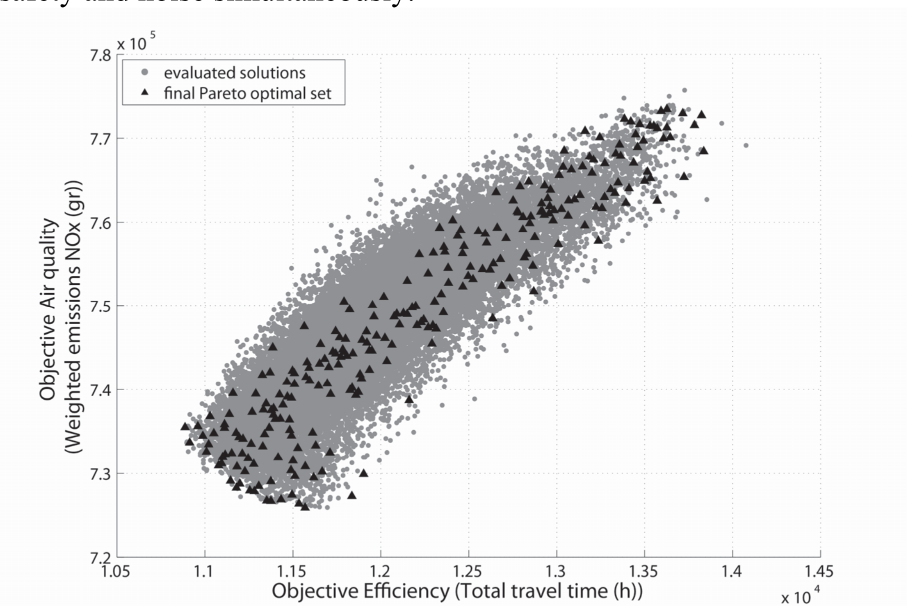
For the optimization, the NSGAII solution approach is used, which settings are based on the research presented in Chapter 5. The initial mutation probability ρ_{mut}^{init} was 0.05, which decreased every generation with 5% for the first 10 generations. The archive size $W_u = 250$ and number of generations $H = 100$, resulting in 25,000 evaluated solutions after the initialization. Based on the S-metric the algorithm converged after 100 generations.

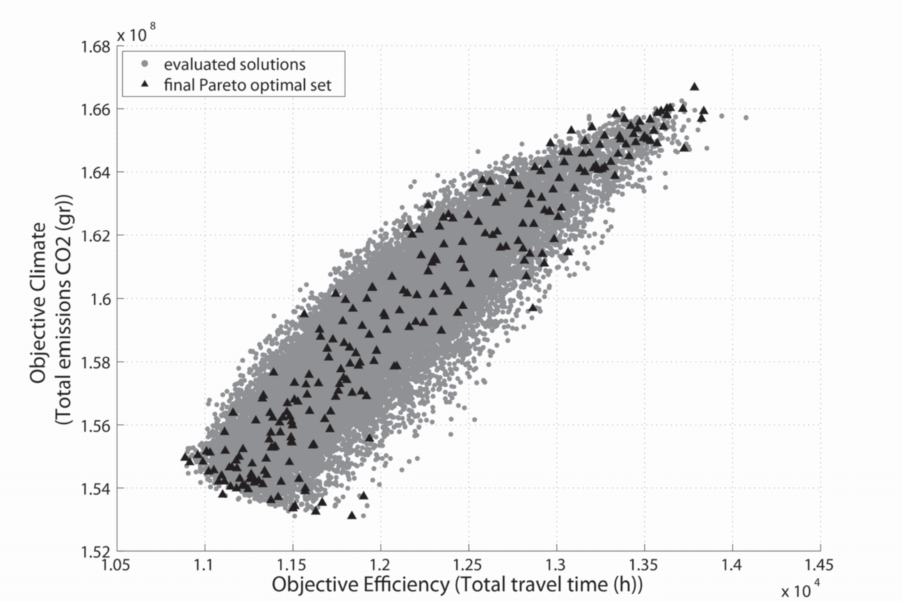
All five objectives were used to determine the Pareto optimal set. Within the analysis the final Pareto optimal set provided by the NSGAII algorithm is used. This means that this set comprises 250 Pareto optimal solutions. Based on this Pareto optimal set, the average trade-offs are determined and the performance of the optimal designs for the individual objectives (i.e. the optimal solutions for the individual objectives and the consequences for the other objectives). Additionally, the same aspects as the objective functions for parts of the network (and not weighted) are calculated to analyze the results in more detail. Highway, rural road, ring road, urban roads, inner city ring road and all radial roads (combined and separated) are distinguished. Vehicle kilometers, travel times, NO_x emissions, CO_2 emissions, noise emissions and number of injury accidents are analyzed for these parts of the network. Using cluster analysis, in this case *k*-means clustering, the Pareto optimal solutions are clustered in the total objective space (i.e. solutions that perform similar on the objectives are clustered) to be able to present the results in a comprehensive way. Because the Euclidean distance is used within the *k*-means clustering, the results on the different objectives are normalized by scoring them between 0 and 1 in which 0 represents the minimum score (best performing solution) and 1 the maximum score on that objective (worst performing solution). Using this clustering technique, means implicitly that all objectives are weighted equally after normalization to form distinctive clusters considering all dimensions and avoids that certain objectives prevail. The outcome of the objectives and indicators for the different clusters are analyzed to determine the consequences of the trade-offs. Within the clusters the indicators and solutions are analyzed also for the different parts of the network to determine to what degree different solutions can result to similar outcome in the objective space.

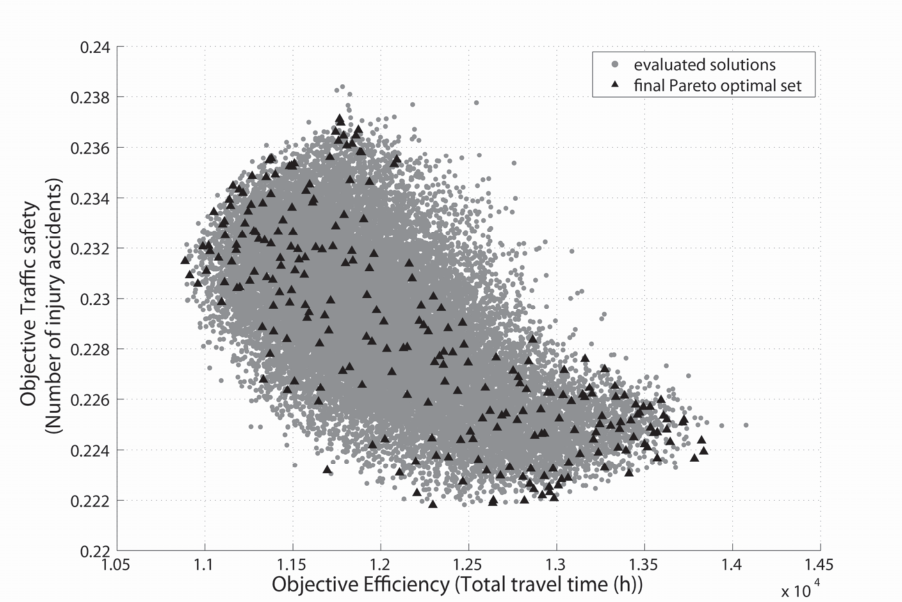
7.3.2 Results

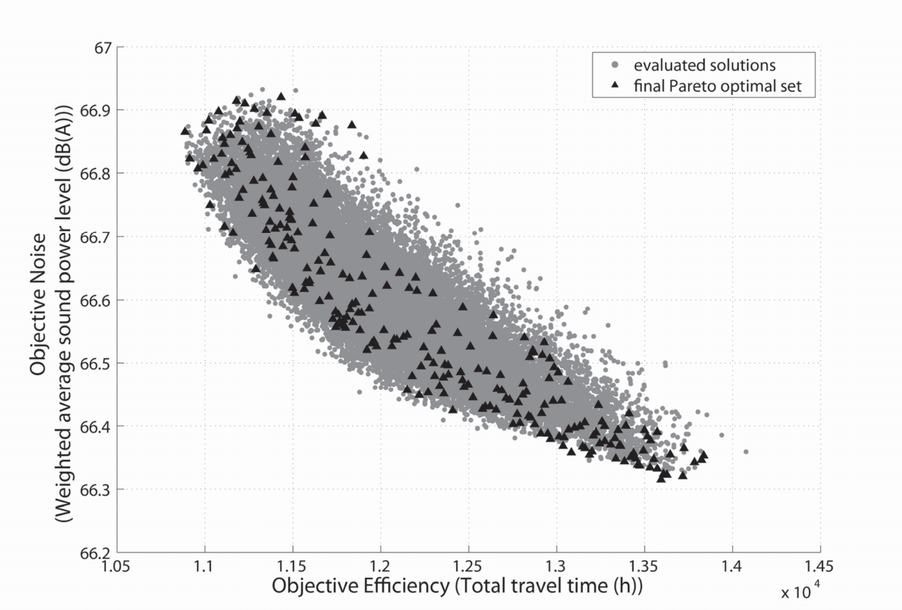
Pareto optimal solutions

Figure 7.11 shows all Pareto optimal solutions found in two dimensional plots. Note that these are the resulting Pareto optimal solutions if optimizing efficiency, air quality, climate, traffic safety and noise simultaneously.




x 10^8
evaluated solutions
final Pareto optimal set
Objective Climate
(Total emissions CO2 (gr))
1.68
1.66
1.64
1.62
1.6
1.58
1.56
1.54
1.52
1.05
1.1
1.15
1.2
1.25
1.3
1.35
1.4
1.45
Objective Efficiency (Total travel time (h))
x 10^4


evaluated solutions
final Pareto optimal set
Objective Traffic safety
(Number of injury accidents)
0.24
0.238
0.236
0.234
0.232
0.23
0.228
0.226
0.224
0.222
0.22
1.05
1.1
1.15
1.2
1.25
1.3
1.35
1.4
1.45
Objective Efficiency (Total travel time (h))
x 10^4


evaluated solutions
final Pareto optimal set
Objective Noise
(Weighted average sound power level (dB(A)))
67
66.9
66.8
66.7
66.6
66.5
66.4
66.3
66.2
1.05
1.1
1.15
1.2
1.25
1.3
1.35
1.4
1.45
Objective Efficiency (Total travel time (h))
x 10^4

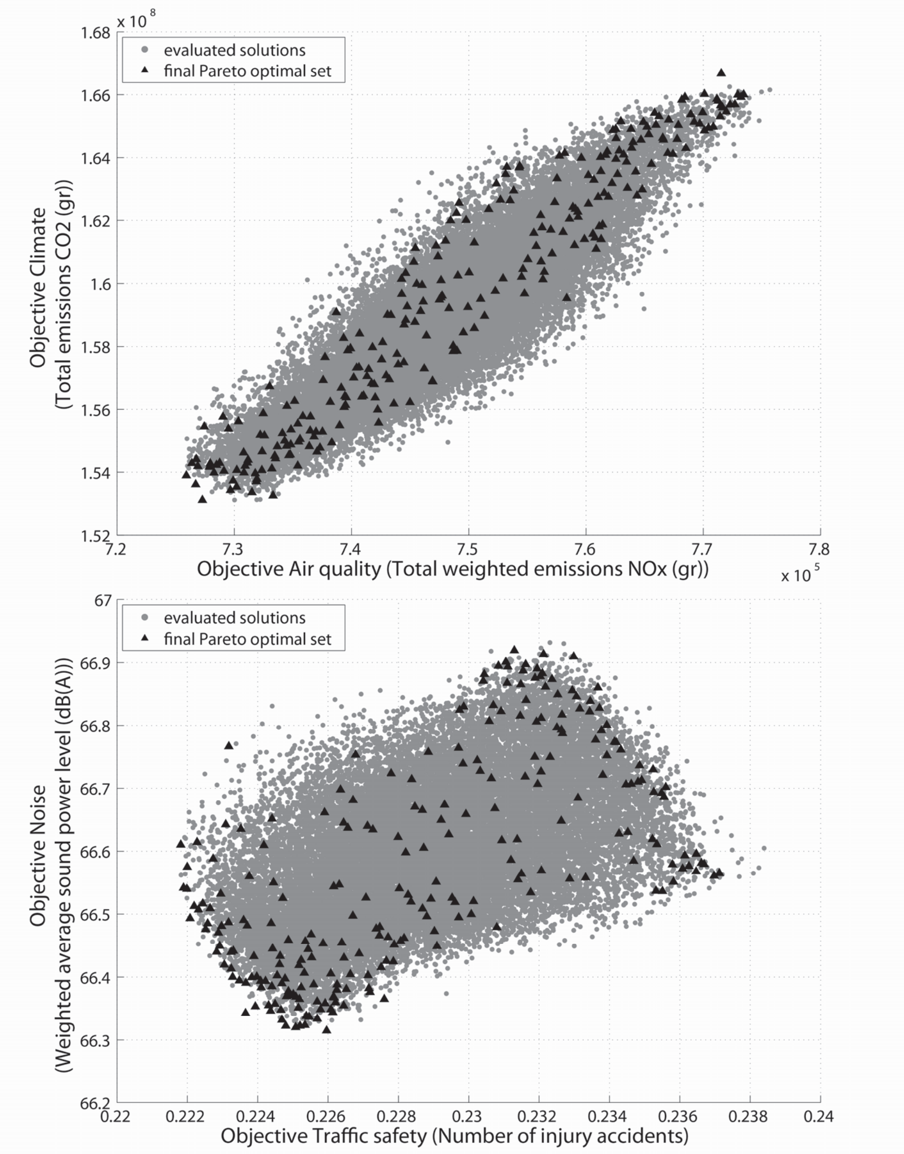


Figure 7.11 Pareto optimal solutions.

As depicted, the objectives efficiency, climate and air quality are mainly aligned and mainly opposed to traffic safety and noise. Note that for the assessment of noise the RMV method is used in this case. The objectives traffic safety and noise are neither aligned, nor opposed. These results are similar for this case as found previously in the first case. However, in this case there is not one single solution that optimizes the objective efficiency as well as the objective climate. This will be addressed, when discussing the optimal designs.

Optimal designs

Although there are aligned objectives, this does not mean that there is one single solution that optimizes the three aligned objectives simultaneously. The solution that minimizes NO_x emissions, for example, results in approximately 6% higher total travel time; in vehicle loss hours this is an increase of 28%. Table 7.11 presents the interaction between the externalities, in which the columns represent the performance of an optimal design for a certain objective. Although the average possible reductions in externalities are small compared to efficiency, the local differences are larger. The total emission of NO_x when optimizing air quality is for example 3.2% lower in highly urbanized areas compared to the performance of the optimal design for efficiency.

Table 7.11 Performance optimal designs

	Optimal design for objective				
	Efficiency	**Air quality**	**Climate**	**Traffic safety**	**Noise**
Efficiency	**100.0**	106.3	108.7	112.9	124.9
Air quality	101.3	**100.0**	100.2	103.0	106.5
Climate	101.2	100.5	**100.0**	104.2	108.4
Traffic safety	104.4	104.4	104.5	**100.0**	101.9
Noise	100.8	100.8	100.8	100.4	**100.0**

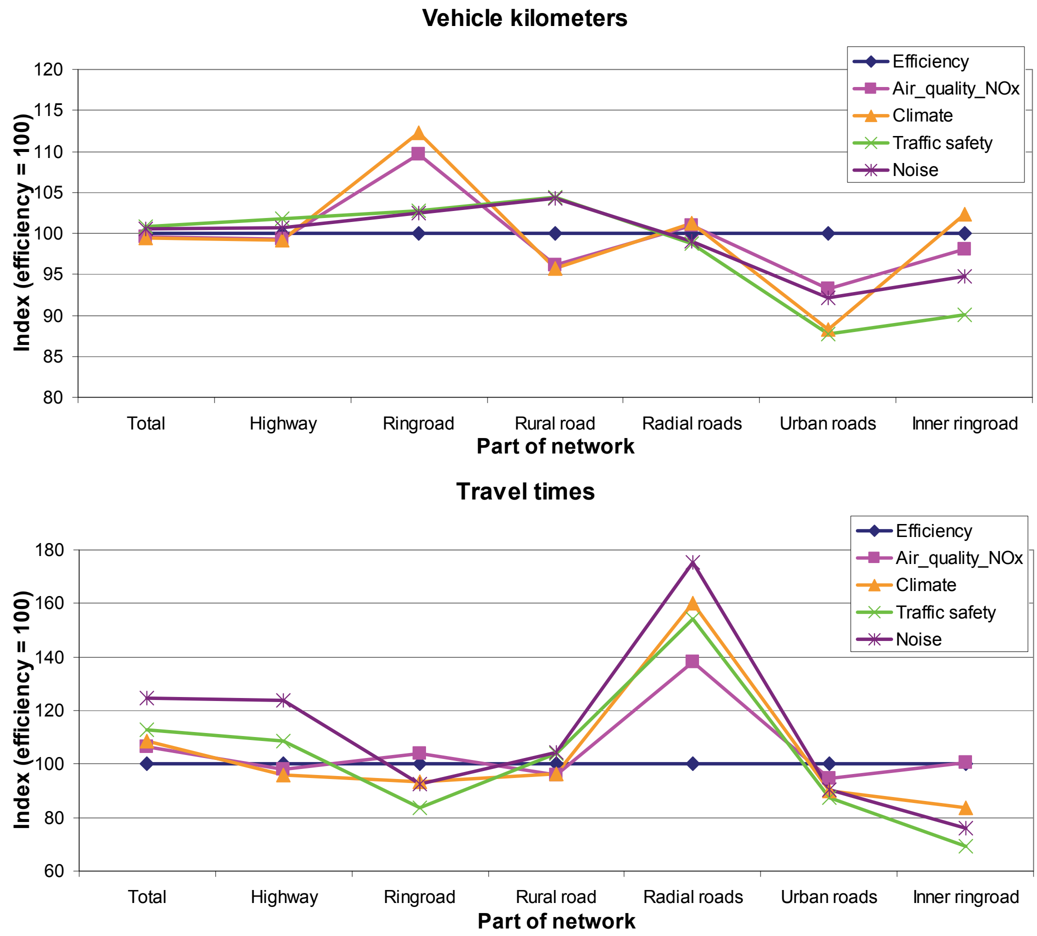


Figure 7.12 Travel times for parts of the network

Figure 7.12 presents the relative performance of the optimal designs on vehicle kilometers and travel times for parts of the network (see Figure 7.10 for the distinguished parts). In this figure the optimal design for efficiency is the reference case, which means for example that the vehicle kilometers as well as the travel times on the urban roads are lower for all other optimal designs. Analyzing the optimal designs for the different road segments shows that also in this case optimizing efficiency aims at avoiding congestion using full capacity of the available routes (urban routes as well) and trying to assign the available capacity in such a way that also on a local level delay is minimized (distributed over directions). The travel times on the radial roads are in this solution much lower than the other optimal designs. Avoiding congestion is also good for minimizing CO_2 emissions, however, the optimal design for emissions queues certain directions in favor of others and by doing this also avoids detours and congestion on other parts of the network. The queued directions are primarily the directions that do not affect other parts of the network (spillback) and therefore the optimal design for emissions accepts congestion on specific locations in the network, while efficiency will distribute the delays more. However, in this case the emissions on the ring road (speed limit of 80 km/h) in free flow conditions are also lower than on urban roads (speed limit 50 km/h) in free flow conditions. Therefore, the optimal design for climate also aims at maximizing throughput on the ring road to maximize use of this road. The same goes for minimizing NO_x emissions, but now the optimal design searches for the best trade-off between minimizing traffic using the urban roads and the rural road and the queued direction is also influenced by the level of urbanization of the upstream links. This also has consequences for the deployment of specific traffic signals, accepting congestion on the ring road in favor of less congestion on urban roads. This means that the concept of metering traffic (possibly in combination with buffering) at specific locations can be interesting to reduce emissions. Traffic safety aims at maximizing the use of the relatively safe highway route and avoiding use of the urban routes. Optimizing noise aims at lowering the driving speeds as much as possible and also avoiding traffic using the urban routes.

Trade-offs

Based on the Pareto optimal set, the average trade-offs between the different objectives are also calculated for this case. The average trade-offs are presented in Table 7.12 (bold figures). This means for example that in this numerical case it is possible to reduce 1.95 kg CO_2 emissions, accepting an increase of 1 hour of total vehicle loss hours (or 5.13×10^{-4} hour, accepting an increase of 1 gram CO_2 emissions), or 568 gram CO_2 emissions, accepting 1 gram more weighted NO_x emissions. Translating these trade-offs assuming 200 morning rush hours a year and knowing that the total travel demand is 45,218 vehicles every rush hour, it is possible to reduce approximately 5 ton CO_2 accepting an average increase of travel time of 1 second per vehicle per rush hour. The fact that these are average trade-offs means that an average increase of 1 second is the result of some road users who will be confronted with more delay and some possibly with shorter travel times. Note that these average trade-offs are limited by the different optimal designs (i.e. these are the boundaries) and are average trade-offs determined by comparison of the performance of the optimal designs for two objectives. The trade-offs between these two will also result in effects on other objectives (positively or negatively), which are presented in Table 7.12 as well. These effects on other objectives are related to the level in which the different objectives are aligned or opposed as presented in Figure 7.11. The average trade-offs in this case are comparable in terms of order of magnitude (i.e. all average trade-offs differ less than a factor 3) with those found for test case 1. However there are also some large differences and in some cases opposed effects related to the impact at the other objectives. In test case 1 for example, the optimal design for noise results in lower total travel times than the optimal design for traffic safety, while in this case the optimal design for traffic safety results in lower total travel times than noise.

Table 7.12 Average trade-offs between objectives.

	Efficiency (1 hour)			
	Air quality	**Climate**	**Traffic safety**	**Noise**
Air quality	**-1.40E+01**	-8.65E+00	8.61E+00	1.39E+01
Climate	-1.57E+03	**-1.95E+03**	3.26E+03	4.05E+03
Traffic safety	2.18E-07	4.26E-07	**-6.86E-06**	-2.04E-06
Noise	-3.66E-05	1.07E-05	-1.81E-04	**-2.03E-04**
	Air quality (1 gram)			
	Efficiency	**Climate**	**Traffic safety**	**Noise**
Efficiency	**-7.13E-02**	1.94E-01	3.35E-02	4.28E-02
Climate	1.12E+02	**-5.68E+02**	2.61E+02	2.54E+02
Traffic safety	-1.55E-08	1.86E-07	**-4.52E-07**	-1.20E-07
Noise	2.61E-06	2.56E-05	-1.06E-05	**-1.11E-05**

	Climate (1 gram)			
	Efficiency	**Air quality**	**Traffic safety**	**Noise**
Efficiency	**-5.13E-04**	-3.42E-04	7.15E-05	1.37E-04
Air quality	4.44E-03	**-1.76E-03**	3.16E-03	3.59E-03
Traffic safety	-2.19E-10	-3.28E-10	**-1.56E-09**	-4.63E-10
Noise	-5.52E-09	-4.52E-08	-4.12E-08	**-4.38E-08**
	Traffic safety (1 injury accident)			
	Efficiency	**Air quality**	**Climate**	**Noise**
Efficiency	**-1.46E+05**	-7.40E+04	-4.57E+04	3.13E+05
Air quality	-1.26E+06	**-2.21E+06**	-2.02E+06	6.18E+06
Climate	-4.75E+08	-5.77E+08	**-6.39E+08**	1.54E+09
Noise	2.64E+01	2.34E+01	2.63E+01	**-7.13E+01**
	Noise (1 dB(A))			
	Efficiency	**Air quality**	**Climate**	**Traffic safety**
Efficiency	**-4.92E+03**	-3.85E+03	-3.14E+03	-4.39E+03
Air quality	-6.85E+04	**-9.00E+04**	-8.19E+04	-8.67E+04
Climate	-1.99E+07	-2.29E+07	**-2.28E+07**	-2.16E+07
Traffic safety	1.00E-02	1.08E-02	1.06E-02	**-1.40E-02**

Cluster analysis

The results are also analyzed in more detail. For this, cluster analysis is used, in this case *k*-means clustering, to cluster the solutions in the total objective space. Because the Pareto optimal solutions are equally spread along the efficient frontier, which is also an objective of the solution approach solving the MO NDP, the optimization of the number of clusters using the silhouette width does not yield a significant better performing number of clusters (shown in Chapter 6 for this case). Therefore, this method is used to divide the solutions in an arbitrary number of clusters, in this case ten clusters. To give an idea of the outcome of the clustering procedure, Figure 7.13 shows the results in which every color represents a separate cluster. Here it is presented in two dimensions, however the clustering is performed in the total objective space (i.e. five dimensions).

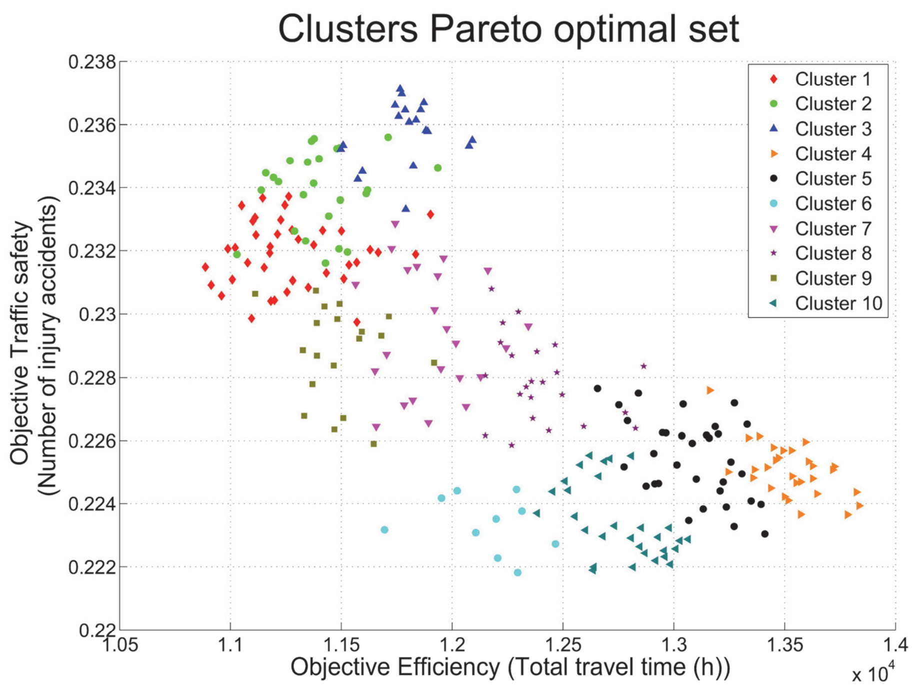


Figure 7.13 Results clustering plotted in two dimensions.

To analyze the outcome of the different clusters on the different objectives, the averages are presented in Figure 7.14 in which these are normalized between 0 and 100 (i.e. the best scoring cluster on an objective scores 0 on that objective and the worst scoring cluster 100). Cluster 1 scores for example well on efficiency, air quality and climate, but cluster 1 is also the worst cluster for noise and scores low on traffic safety. These results show, as concluded earlier, that the objectives efficiency, air quality and climate are aligned and those are opposed to traffic safety and noise. Due to the clustering, the optimal solutions of the aligned objectives are part of the same cluster. However, as shown earlier, the performance of the optimal designs are different, which means that decision makers still need to determine a compensation principle for these objectives to choose the best compromise solution. Using this cluster data, the average trade-offs between the clusters can be determined. For instance, solutions part of cluster 10 compared with cluster 1 results on average in 13% higher travel time, 4% higher weighted NO_x emissions, 6% higher CO_2 emissions, 4% less injury accidents and 1% less weighted sound power level.

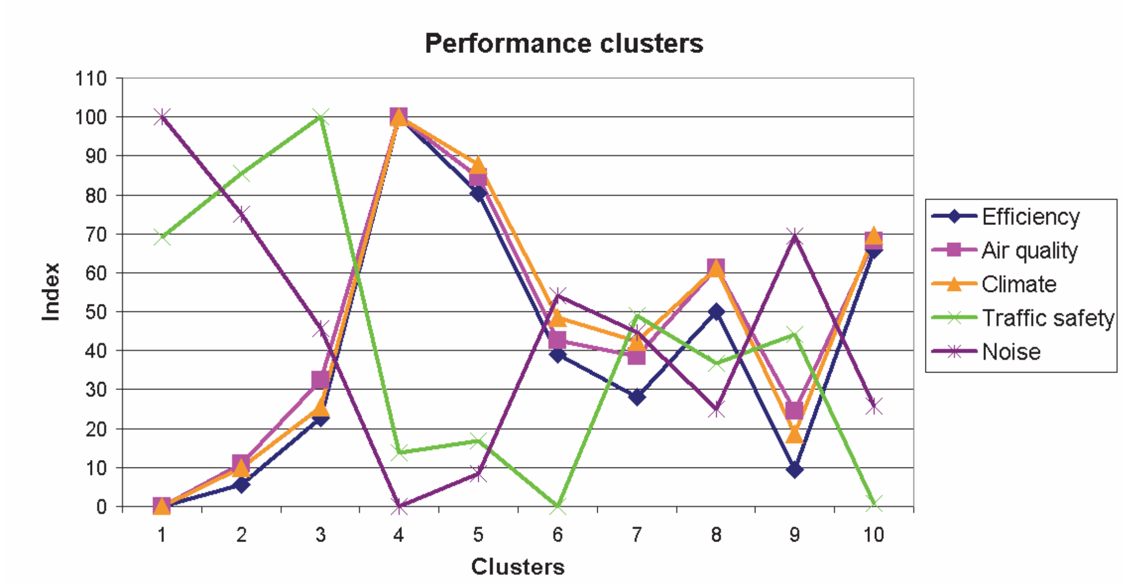


Figure 7.14 Objective scores clusters

Focusing on the different parts of the network, the results show that the differences between the clusters are coherent, which is an indication that there is a correlation between the distances between solutions in objective space and solution space. This means that on average the differences between clusters on the different objectives result in similar results for parts of the network (e.g. clusters performing well on traffic safety all show high emissions on radial roads). The results also shows that the relative largest differences for congestion, air quality and climate between the clusters are on the radial roads (see Figure 7.15). Here, it is for example also shown that the emissions of NO_x on urban roads can be 10% lower compared to cluster 1. On the highway the relative differences are small, however in absolute figures these differences are large and can substantially influence the total outcome of most objectives. In terms of vehicle kilometers the relative differences are larger on the ring road, rural roads and urban roads. The results also show that the clusters that perform better on noise and traffic safety, show relative higher emissions and travel times on the radial roads and rural road and less on the urban roads and ring road. Within the clusters that perform better on noise and traffic safety the measures available, mainly situated on the ring road, meter traffic on the radial roads improving the level of service on the ring road. As a result more traffic uses the rural road to approach the city on the west side and less traffic is using the urban roads.

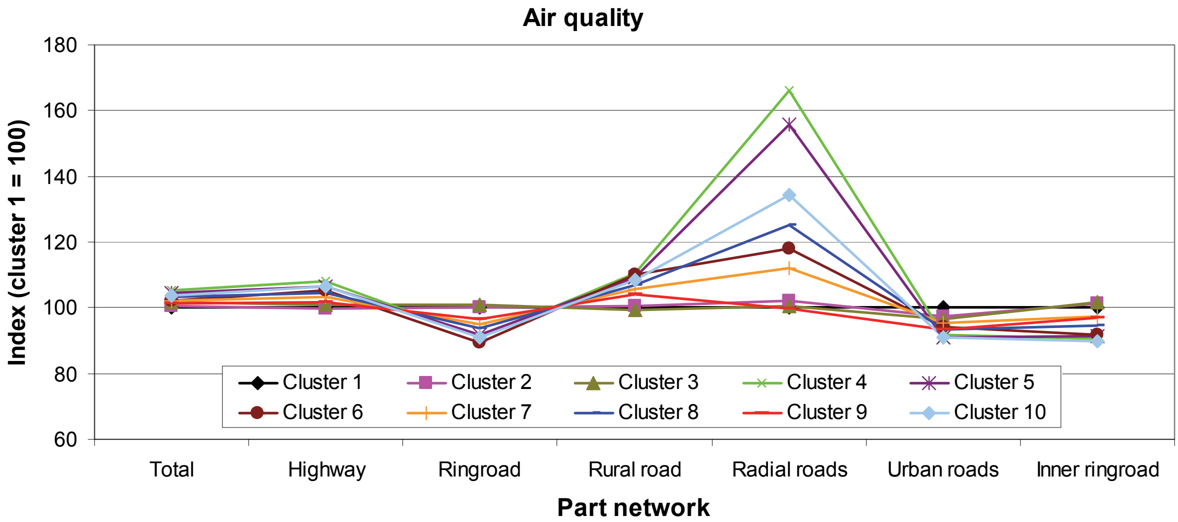


Figure 7.15 Objectives for different network parts per cluster

Analysis within cluster

The clusters show on average the choices available for optimization of the different objectives and the trade-offs associated with them. The analysis of the clusters already gave an indication that there is a correlation between the distances in objective and solution space. Computing the correlation results in a significant correlation coefficient 0.85. However, it is still possibly true that two distinct solutions in the solution space can result in similar performance in the objective space. As discussed in Chapter 6, this knowledge is relevant for the decision making process, because other aspects (e.g. social support) that are not taken into account in the optimization process can be addressed. If for example there are two solutions that result in similar performance in the objective space, but are distinct in terms of equity (i.e. the differences to what extent certain traffic flows are metered) or complexity (i.e. variation of settings measures over time), the decision maker can use this information to choose the best solution.

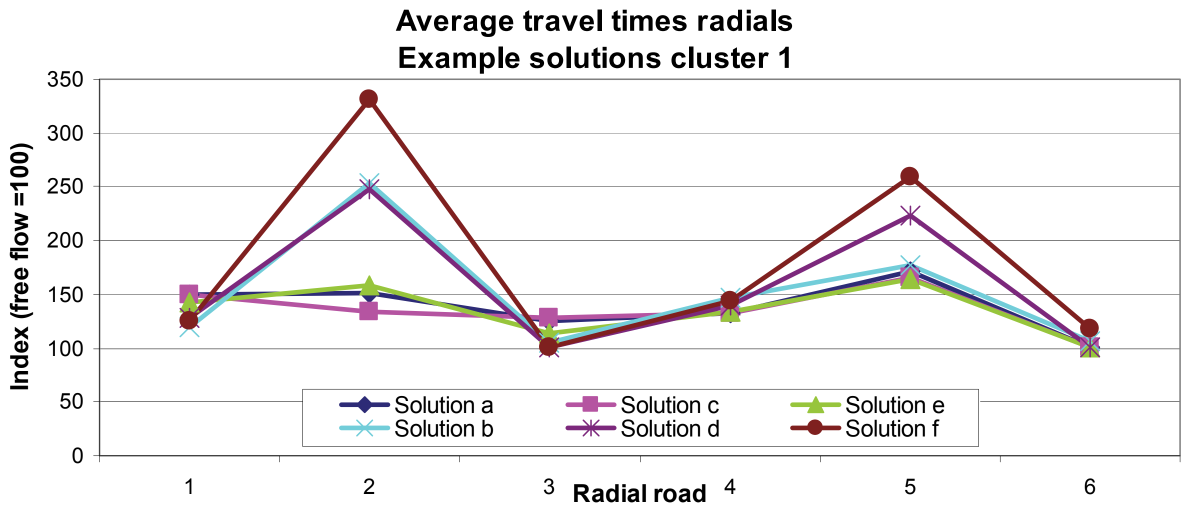


Figure 7.16 Travel times radial roads for different solutions cluster 1

To illustrate the differences within the clusters, cluster 1 is further analyzed using the results of the different solutions for the different radials. The radials are chosen, while on these parts of the network the relative differences are the largest and most DTM measures available influence these radials. In Figure 7.16 the travel times of six solutions part of cluster 1 for the different radial roads (see Figure 7.10 for numbering radial roads) are presented. These results illustrate that solutions that result in similar performance on a network level can be distinct in equity. There are solutions in which traffic flows using radial 2 or 5 are metered, while there are also solutions part of the same cluster with average delays that are more equally spread over all radials.

7.3.3 Conclusions

In the case study for a realistic network it is shown that the objectives efficiency, climate and air quality are mainly aligned and mainly opposed to traffic safety and noise, which was also true for case 1. The objectives traffic safety and noise are neither aligned, nor opposed. However, in this case there was no single solution optimizing efficiency and climate simultaneously, which means trade-offs exist between all five objectives. The optimal designs showed that avoiding congestion is also good for air quality and climate. However, the optimal solutions for air quality and climate do meter certain flows on specific locations to avoid detouring and congestion downstream and increase the use of the ring road, while the optimal solution for efficiency distributes delays more. Using cluster analysis the Pareto optimal set was further analyzed also for parts of the network. The results show that the differences between the clusters are coherent on average and there is also a strong correlation between the distances between solutions in objective space and their distances in solution space. However, this test case showed that solutions can still be distinct and result in similar performance in objective space, which means additional criteria can be used like equity to choose the best compromise solution.

7.4 Concluding remarks

In this chapter various case studies are presented using the synthetic network and the realistic network of the city of Almelo. These studies show that the objectives concerning efficiency, climate and air quality are aligned, but the optimal designs are not exactly the same. As a result the possible improvements on climate and air quality are relatively small on network level compared to the performance of the optimal design of efficiency, but the differences can be large at certain locations. It is also of importance to note that in this case efficiency is optimized on a network level, while in practice this is still rarely the case. Comparison with local optimization of efficiency will probably result in larger differences, because for air quality it is for example better to avoid traffic using urban roads, while for efficiency the optimal use of full capacity (urban roads as well) will lead to improvements. The objectives noise and efficiency are more opposed to efficiency, which also results in larger differences. In addition, al these effects should also be valued in the perspective of what a certain reduction or increase means in terms of for example fatalities, change in life expectancy, people annoyed or policy objectives related to climate. Assuming that it is possible to reduce at least 1% (based on results second case) of total CO_2 emissions of road traffic in the Netherlands by changing the deployment of DTM measures means for example that approximately 0.3 Mton of CO_2 emissions can be avoided on a yearly basis.

The relation between traffic dynamics and the externalities are partly presented in Chapter 3 and 4 in which the externalities and assessment methods are described. In general, efficiency improves when congestion is avoided, which is also better for the emissions of substances. However when the speed is high (approximately above 80 km/h) emissions increase. For noise, reducing speed also reduces sound emissions. However, when traffic conditions are saturated, propulsion noise is the dominant source for sound and increases as a result of more accelerations and decelerations. For highways the emission of sound is lower for saturated conditions than free flow conditions, but for urban roads the emissions of sound can be higher in saturated conditions compared to free flow conditions. Avoiding congestion on urban roads can therefore also be relevant to improve noise. For traffic safety the impact of local traffic dynamics is not incorporated in the assessment method, but it is known that higher speeds results in an increase in risk.

Complexity increases when considering the differences between cars and trucks, especially for externalities, but also when taking into account the interaction between these two vehicle classes. For efficiency a high percentage of trucks can increase travel times, because it becomes more difficult to overtake these vehicles, but also as a result of shock waves. For the emissions of substances, the relation between traffic dynamics and emissions is similar for trucks as for cars, however the emissions by trucks in absolute values is much higher than for cars (i.e. for CO_2 5 times higher and for NO_x 25 times higher for free flow, heavy and saturated traffic conditions and for CO_2 8 times higher and for NO_x even 45 times higher for stop and go conditions). This means that the contribution of trucks in emissions of substances is significant and can be even dominant if it is assumed that the percentage of trucks is on average 10% of traffic. However, higher percentages of trucks can also decrease speeds of cars at highways, which can decrease the emissions of cars. Propulsion noise is the dominant source of sound emission of trucks at higher speeds as well (approximately till 80 km/h, which in the Netherlands is the maximum speed limit for trucks at highways). As a result sound emissions of trucks in stop and go traffic conditions are higher for highway roads than for free flow conditions. The absolute values of sound emissions are also higher for trucks than for cars (can be 20% higher measured in dB in stop and go traffic conditions and 10% in free flow conditions). However, because noise is measured on a logarithmic scale the influence of trucks on the sound emissions can be large as well (i.e. in sound energy emissions of trucks can be 10 times higher in stop and go traffic conditions). However, in free flow conditions the energy emissions of trucks is 4 times higher. As a result the emission of sound of the combination of trucks and cars is still higher in free flow conditions (assuming a share of 10% trucks) than it is in stop and go traffic conditions. In general, the influence of the percentage of trucks is therefore larger for the emissions of substances than it is for the emissions of sound. For traffic safety, less is known about the influence of trucks. It is known that higher percentages of trucks on highways can reduce the number of accidents, however if trucks are involved in accidents the severity of accidents is often higher.

The additional complexity of this research is the incorporation of interaction between links and the route choice effects of a certain deployment of DTM measures. For noise as well as air quality, the location of emissions are relevant, because it is important to take into account the number of people who are confronted with these emission. For climate the location is not relevant, because the global emission is important. However, for all three objectives the absolute level of emissions differs per road type or speed limit. For emissions of substances for example the free flow emissions at a 80 km/h road are lower than at 50 km/h road, while for noise emissions it is exactly the other way round. For traffic safety the risk figures differ per road type, which means that there are relatively safe roads and relatively unsafe roads. To be able to seduce traffic using the preferred roads to achieve preferred traffic conditions as well, it is needed to influence the utilities (i.e. travel times) of the various routes using the DTM measures. However, achieving such traffic conditions is less trivial than one might expect, because of the interactions between roads. In test case 1 it is for example shown that giving full capacity does not result in the optimal situation for efficiency, because as a result not all routes are used and therefore not the available capacity. All test cases in this research showed that the objectives efficiency, climate and air quality are mainly aligned and mainly opposed to traffic safety and noise, but there exist not one single solution that optimizes all objectives simultaneously. Therefore compensation principles are needed to determine the best compromise solution. However, given the relations between the objectives and results found in the presented cases it is possible to formulate a general strategy that can be used in many cases in practice to reduce externalities. Because highways are often situated in less urbanized areas and are the relative safest roads, a general strategy could be to facilitate traffic on higher order roads possibly decreasing the speed limit and metering and buffering vehicles at smart locations (often at the borders of the urbanized areas), while facilitating traffic in the city avoiding congestion. Metering of traffic should be used to avoid congestion in urban areas and to influence route choice of traffic in such a way that mainly the higher order roads are used. However, where traffic should be exactly metered and buffered and to what extent depends on the routes available, spatial planning and demand in the specific case and can therefore be complex to determine in practice.

There still remain issues that are of interest for further research. In this research a pragmatic weighting is used for noise and air quality. It can be expected that other weights will result in other optimal designs and other relations between the objectives. If, for example, the emissions on urban roads are weighted heavier, it can be expected that air quality and traffic safety are less opposed, because in that case using the relative safer highways are also a more important aim for air quality. In addition, the objective function in this research are formulated as network performance measures, while in other cases it can be of interest to reduce externalities at specific locations (e.g. because of air quality problems). Finally, the assessment of traffic safety is less dependent on traffic dynamics than the other externalities in this research. Although explained why this was not possible, it is known, at least for motorways, that risk increases when speed increases and when speed differences are larger. Unfortunately, there is inconsistency in found effect of congestion on traffic safety (Marchesini and Weijermars, 2010; Aarts and Van Schagen, 2006). If the relation between speed and accidents holds for all road types, it can be expected that traffic safety will be more aligned with noise.

Chapter 8

Conclusions and further research

In het land der blinden is eenoog koning, maar hij blijft een eenoog
In the land of the blind, the one-eyed man is king, but he remains a one eyed man
Johan Cruijff

In Chapter 1 the context of this research was presented as well as the research objectives, scope and design. Chapter 2 provided background about research on the deployment of DTM measures and research on NDP. General information on externalities and ways to assess these using DTA models is extensively discussed in Chapter 3. This knowledge was combined in Chapter 4 to present the general framework of the dynamic MO NDP used in this research. To solve this MO NDP several solution approaches were developed and tested of which the results were presented in Chapter 5. In this research the optimization problem is formulated as a multi-objective optimization problem to be able to learn about the problem at hand and solutions possible before decisions have to be made. Therefore, Chapter 6 discussed the information that is contained in the Pareto optimal set, which can be used in the decision making process. Chapter 6 also presents a framework for an interactive decision support tool and discussion and application of several pruning and ranking methods that can be used in such tool. Finally, in Chapter 7 the outcome of several optimizations using two cases were presented to show the actual outcome of such optimization to gain insights in how to deploy DTM measures on network level to optimize externalities on a network level.

This final chapter is divided in three sections. In the first section the thesis research is summarized and conclusions are drawn from the perspective of the research objective formulated in Chapter 1. Then, the overall research approach and findings are reflected upon, leading to the possible implications of this research and recommendations for future research directions. The presented conclusions and recommendations are relevant for practitioners as well as scientists.

8.1 Conclusions

This thesis provides a suitable approach to optimize efficiency as well as externalities on network level taking behavioral responses of road user (i.e. route choice effects) into account and presents insights in DTM strategies when externalities are incorporated as objectives. Traditional DTM is focused on accessibility, but it has been acknowledged that DTM measures can be powerful instruments to reduce externalities. Various initiatives in research and practice have shown that externalities can be reduced using DTM measures. These measures can be used to influence traffic conditions and these conditions, especially the traffic dynamics, are important explanatory variables for externalities. DTM measures such as traffic signals and VSL can be used to reduce externalities on a local level, but also on a network level influencing the amount of traffic using different road types. Taking into account multiple objectives instead of one, also introduces additional difficulties, because at the end one strategy has to be chosen to implement. To be able to choose such strategy the decision makers have to determine which compensation principle to use, which is often difficult to determine in advance. Knowledge on the consequences of choosing a compensation principle and the possibility to learn about the problems and solutions, could support this decision. Providing this knowledge needs a multi-objective optimization instead of a single-objective optimization in which the various objectives are combined. To assess the effects of measures often transport models are used. In general, DTA models are more suitable to estimate the effects of ITS than STA models, since time variability plays a significant role in most cases. In addition, the limitations of STA particular for over-saturated traffic conditions are widely recognized and DTM measures are often used to improve these kinds of traffic conditions. In this case the usage of DTA models, or at least the dynamic network loading and suitable effect models to quantify the effects on externalities, is also needed to be able to address the effect of DTM measures on traffic dynamics and therefore externalities. Research on DTM strategies taking behavioral responses into account are rare and incorporation of objectives concerning externalities taking explicitly the effects on traffic dynamics into account has not been investigated earlier. Therefore no knowledge was available on how the various externalities are related and what the possible effects and consequences are when a certain strategy is adopted. Formulating the resulting multi-objective optimization problem as a dynamic MO NDP and solving this problem results in finding the Pareto optimal set of solutions. This set contains valuable information that is used to provide the insights in how to deploy DTM measures on network level and can also be used as an input for decision support.

However, to be able to provide these insights, several additional challenges had to be addressed in this research. First of all a suitable modeling framework had to be formulated in which modeling of the externalities using DTA models was the main challenge. Second, a solution approach had to be found that could solve the dynamic MO NDP. To be able to choose the best strategy given the multiple objectives, knowledge on the suitability of methods to assist, is needed, which is the third challenge. Finally, the fourth challenge was to apply the approach in test cases, to be able to provide the insights.

Modeling framework
To solve the dynamic MO NDP, it has been formulated as a bi-level optimization problem in which at the upper level the system objectives (i.e. externalities as well as efficiency) are optimized by the road management authorities and at the lower level the road user optimize their own objectives (i.e. minimizing their own travel times). To solve the lower level problem a dynamic UE problem is solved using the Streamline macroscopic DTA model.

The system objectives are formulated as network performance measures to reduce complexity, resulting in one single objective function per externality and one for efficiency. For efficiency minimizing total travel times is used, which is suitable in his research because of the assumption of fixed demand. For climate the total CO_2 emissions and for traffic safety the total number of injury accidents is used. For noise and air quality a weighted function is used, in which the weights depend on the level of urbanization. For these objectives the location where the substances are or sound is emitted, is of interest, reflecting the number of people who are affected. For air quality the weighted sum of NO_x or the weighted sum of PM_{10} is proposed and for noise the average weighted sound power level. By using a DTA model and appropriate effect models the impact of traffic dynamics on externalities are taken into account.

To calculate the objective functions, the DTA model, used to solve the lower level optimization problem, is connected with effect models. Based on an extensive literature review on modeling externalities using DTA models presented in Chapter 3, it can be concluded that most efforts in assessing external effects with DTA models use microscopic DTA models. However, the assessment on this detailed level does not necessarily means an improvement of the estimates and can result in apparent accuracy. Because macroscopic DTA models are more suitable to use for larger networks, effect models are needed that can be used in conjunction with these types of DTA models. The interconnection between DTA models and effect models should be balanced, depending on the accuracy of the output of the DTA model and the needed accuracy of the input of these models. Based on the models and research available, it is found that for traffic safety there is still a gap in knowledge to assess traffic safety with DTA models. It would be recommendable to use APMs incorporating traffic dynamics as explanatory variables in conjunction with macroscopic DTA models. However, because there does not exist a complete set of APMs covering all road types, incorporating traffic dynamics as well, a risk based model is used in this research to assess traffic safety. For modeling emissions, traffic situation based models are most suitable for macroscopic DTA models and therefore used in this research. Although relatively little research is done in assessing noise in conjunction with DTA models, the methods available to determine the source emissions in conjunction with dynamic models are suitable. However, in saturated traffic conditions propulsion noise increases due to accelerations and can be dominant at those low speeds. Often source emission models use a correction factor for accelerations, because the emission function calculates the emissions based on an instantaneous constant speed (uninterrupted flow). Uncertainties in estimating accelerations and decelerations based on the outcome of macroscopic DTA models is probably higher than the impact of accelerations and decelerations on sound power level. However, the AR-INTERIM-CM (based on French Guide du Bruit) does include the impact of accelerations in the emission function (separate emission functions and therefore traffic situation based). In this research two methods are used; the RMV model without taking the effect of accelerations and decelerations into account and the AR-INTERIM-CM model, which does.

The decision variables in this dynamic MO NDP are the deployment of DTM measures. Because the aim of this research is to find strategies for the deployment of DTM measures on a network level and to decrease the number of decision variables, the DTM measures are modeled in a simplified way by using link characteristics. These link characteristics include the capacity, outflow capacity, number of lanes, free speed, speed at capacity and jam density, and are captured in a fundamental diagram. This means that the eventual strategy found provides the services needed (e.g. improving throughput, metering and or buffering traffic) at specific locations, which have to be translated into the actual available parameters of the

DTM measures (e.g. translating given capacity to a certain direction into green times). In addition, only traffic control measures are considered that can actually influence supply of infrastructure. To reduce the number of needed decision variables even more, an approach is used connecting direction of traffic signals in such a way that makes it possible defining the settings using 1 decision variable on an interval scale. Being able to define the settings on an interval scale, is also relevant for estimating surrogate models with limited variables,

Solution approach
Multi-objective optimization deals with more than one objective function, which in this research all needed to be minimized. Solving a multi-objective optimization problem results in the Pareto optimal set of solutions that can be used in the decision making process, but also in this research to learn about the problem and solutions. Solving NDP is normally difficult, because it is non-convex and non-differentiable and has been proven to be NP-hard. All research that did not reformulate the problem (using additional assumptions to simplify the problem), therefore use heuristics to solve it. For the dynamic MO NDP no scalable approaches (i.e. only suitable for single destination networks) are available in which the problem can be reformulated in such a way, it can be solved efficiently. In various studies addressing NDP, different algorithms are tested and compared. In most cases GA outperformed the other algorithms and GA is also often used in NDP research in which no algorithms are compared. The GA approach has been proven to be capable of solving SO NDP as well as MO NDP, NDP in which DTM measures are the decision variables and NDP in which externalities are the objectives, which means GAs can deal with the function types associated with NDP. Because many MOGAs have been proposed three algorithms that provide excellent results compared to others, have been compared for the dynamic MO NDP. The results indicate that the SPEA2 and mainly the SPEA2+ approach are able to obtain a more diverse solution set in the objective space as well as in the solution space than the NSGAII approach. However, the NSGAII approach is able to obtain a slightly larger space coverage. The SPEA2+ approach is also able to cover more of the sets attained by the NSGAII and SPEA2 approach, but the NSGAII approach obtains a larger space coverage difference. On average, the SPEA2+ outperforms the SPEA2 in this optimization problem on all used measures. Comparing NSGAII and SPEA2+, there is no clear evidence of one approach outperforming the other.

The heuristics do require a large number of function evaluations. Every function evaluation requires solving the dynamic UE problem by the DTA model, which is computationally expensive, especially in large scale real world applications. To relax these time-consuming optimization procedures, three algorithms that use RSM to estimate a surrogate model are proposed and compared. All algorithms used the SPEA2+ algorithm as a basis, because it showed more diversity in solution space, which is relevant for the estimation of the surrogate model. Comparison of the algorithms given a fixed computation time budget shows that the use of RSM methods does find solutions in similar parts of the objective space as regular SPEA2+ and therefore does not result in missing relevant parts of the Pareto optimal set. The average performance of the algorithms is similar in which the SPEA2+ pre evaluation FA, in which the proposed children are pre evaluated using the surrogate model to determine if it is exactly evaluated, performs slightly better than regular SPEA2+. The development of the performance measures shows that all three algorithms using RSM methods accelerate the search at the start considerably. With less exact evaluated solutions already good solutions are found. However, the algorithms using these RSM methods tend to converge faster, possibly to a local optimum and therefore loose their head start, because these algorithms depend largely on the quality of the surrogate model. Therefore, these methods are of interest for the dynamic

MO NDP of this research, because for larger networks a limited number exact evaluations can be done and a reasonable performing set of solutions can be satisfactory to determine the interesting strategies. Although, the algorithms using RSM methods all used SPEA2+ as a base case, the methods can be used for other EAs as well.

Decision support
To be able to choose between solutions a compensation principle is needed, which is a public policy decision. The Pareto optimal set contains valuable information to support this decision making process, which allows the decision makers to learn about the problems and solutions before choosing a certain strategy to implement. In addition, multi-objective optimization has the advantage of considering all possible strategies instead of evaluating a few predefined strategies. In this research an interactive decision support tool is proposed, which distinguishes four steps. In the first step a general analysis of the Pareto optimal set provides insights in how the objectives relate, present the upper and lower bound, the optimal designs and possible trade-offs. In the second step the main choices are analyzed possibly based on a pruned Pareto optimal set. Pruning may be useful to circumvent the possible difficulties in analyzing and comprehending the large Pareto optimal set in the decision making process. The third step is used to select the best compromise solutions based on a MCDM method. These best compromise solutions are closer investigated in the fourth and last step to choose the best compromise solutions and therefore strategy to implement possibly using additional criteria like equity, robustness and complexity.

Next to an explanation of the information contained by the Pareto optimal set, relevant for the general analysis, three pruning methods, namely convex hull, clustering and PIT filter, are compared to demonstrate the various outcomes, advantages and disadvantages. Pruning methods reduce the Pareto optimal set retaining distinctive solutions and therefore the main characteristics of the Pareto optimal set as an input for the decision making process. Because in the used case the Pareto optimal set showed an even spread, the *k*-means clustering filter resulted in arbitrary cluster sizes if optimized, using the silhouette width. However, irrespectively if this is also the case in other situations, this method is useful to analyze the main choices by presenting the results in aggregated form to the decision makers. However, because choosing a representative solution for one cluster is not trivial, this method should not be used to select a subset of solutions. The convex hull filter can result in a significant reduction of the Pareto optimal set and is in accordance with ranking methods using linear weighting, but may result in neglecting interesting parts of the objective space. The PIT filter is the most suitable method to choose a subset, because it is related to the changes in trade-offs between solutions and therefore retains the interesting solutions for the decision making process.

In this research also various MCDM are compared to demonstrate the differences in possible outcomes, advantages and disadvantages. The MCDM methods deal with the evaluation of a set of alternatives, using a set of decision criteria, to choose the best or select a few good compromise solutions for closer investigation. These methods are already important instruments for decision making processes in which a predefined set of alternatives are compared. CBA in which the effects are monetized, which means monetary value are used as weighting factors, is an often used appraisal method within the field of traffic and transportation. Application of the CBA method shows that the strategies that minimize total travel time prevail. Travel times turn out to be the most dominant objective, which means that only objectives that are aligned with efficiency will profit to some extent when this method is used. If the decision makers decide that economic trade-off should be the way to rank the solutions, it can be stated that optimizing efficiency will result in the best compromise solution for externalities as well. However, the monetary values often used are debatable and if decision makers want to take externalities into account more seriously, other ranking methods should be considered. There are many ranking methods available, which result in different rankings, even when the same weighting factors are used. All these methods basically try to rank the solutions by comparing the performance of these solutions on the individual objectives. In this research the elementary methods WSM and WPM are applied as well as the often used AHP and the ELECTRE III method, which is an outranking method. These methods are chosen because these are widely used also within the field of transportation and to cover most types appropriate for the data characteristics of the MO NDP (i.e. deterministic with a level of uncertainty). The main difference between the WSM, WPM and AHP ranking methods is the way the objectives are normalized, which obviously influences the outcomes and sensitivity levels for weighting factors. The ELECTRE III is a method that, in contrast to the WSM, WPM and AHP, can take uncertainties into account and is possibly a more suitable method choose a single best compromise solution. However, this method is complex and therefore not transparent. The WSM or AHP method are more transparent methods and therefore possibly more suitable to use in an interactive decision support tool to select the best compromise solutions to investigate further.

Applications

To provide insights on how to deploy DTM measures to optimize externalities on network level, the outcome of test cases using a synthetic network and a realistic network of the city of Almelo is used. In both cases it is shown that the objectives efficiency, air quality and climate are aligned and are opposed to traffic safety and noise. However, there is not one single solution that optimizes all objectives simultaneously, which means there exist trade-offs between all five objectives. Based on the results of the Almelo case emissions of substances can be approximately 1% lower accepting an increase between 6% and 9% in travel times comparing the optimal designs for these objectives. Injury accidents can be 5% lower accepting an increase of 13% in travel times and noise emissions 1% lower accepting an increase of 25% in travel times. Compared with current practice in which most DTM measures are locally optimized or DTM strategies implemented based on expert judgment, the possible improvements are probably larger. Although some of these network effects are small, the local improvements can be substantial. In addition, these results translated in absolute values means that there are serious improvements possible.

The optimal design for efficiency aims for avoiding congestion using full capacity of the available infrastructure. Avoiding congestion is also of importance for the emissions of substances. Because for air quality the emissions in urbanized areas are weighted higher, the optimal design for air quality searches for the best trade-off between avoiding congestion and usage of the urban routes. In the synthetic case the objectives climate and efficiency turned out to be almost co-linear, which was less the case in the realistic case of the city of Almelo. Because in the synthetic case it is assumed that capacity increases when lowering the speed limit and lowering the speed limit also decreases emissions, the optimal designs for efficiency and climate are similar. In the realistic case of the city of Almelo the increase in capacity is not assumed and because of more road types and route choice options the optimal designs for climate and efficiency are less similar. The optimal designs in the realistic case of the city of Almelo showed that avoiding congestion is also good for air quality and climate. However, the optimal solutions for air quality and climate meters certain flows on specific locations to avoid detouring and congestion downstream, and increase the use of the ring road, while the optimal solution for efficiency distributes delays more. For traffic safety the optimal design tries to maximize the use of safest routes (i.e. highway routes), and avoiding urban routes, which are less safe. For noise, the optimal design when using the RMV model aims at lowering speeds as much as possible and avoiding traffic using the urban routes. However, when the increase of propulsion noise in saturated traffic conditions is taken into account using the AR-INTERIM-CM noise model, the optimal design for noise still aims at lowering speeds, but avoiding congestion mainly on urban roads as well. In the latter case noise is therefore less opposed to efficiency than if this effect is not reckoned with. Using cluster analysis the Pareto optimal set was further analyzed also for parts of the network. The results show that the differences between the clusters are coherent on average and there is also a strong correlation between the distances between solutions in objective space and their distances in solution space. However, solutions can still be distinct, while resulting in similar performance in objective space, which means additional criteria like equity can be used to choose the best compromise solution.

The cases in this research showed that there is not one single solution that optimizes all objectives simultaneously. However, given the relations between the objectives it is possible to formulate a general strategy that can be used in many cases in practice to reduce externalities. Because highways are often situated in less urbanized areas and are the relative safest roads, a general strategy could be to facilitate traffic on higher order roads possibly decreasing the speed limit and metering and buffering vehicles at smart locations (often at the borders of the urbanized areas), while facilitating traffic in the city avoiding congestion. The metering of traffic should be used to avoid congestion in urban areas and to influence route choice of traffic in such a way that mainly the higher order roads are used. However, where traffic should be exactly metered and buffered and to what extent depends on the routes available, spatial planning and demand in the specific case and can therefore be complex to determine in practice.

8.2 Implications

The results obtained in this research can also be translated in implications for various aspects in the field of traffic and transport. The closest implication is related to the STM process when a multi-objective optimization is incorporated. All steps distinguished in this process will change and will be less expert judgment based and less “problem-driven”, because in this case the objectives are actually optimized. In the first phase of such process the focus will be to formulate appropriate objective functions, constraints and decision variables. This phase still needs expert judgment (e.g. to be able determine which existing and new measures should be incorporated as decision variables) and requires different skills of the involved parties than in the current process. Although, it is not necessary to negotiate in this first phase about the priorities in objectives, priorities of roads or thresholds as in the original STM process, consensus is needed about the objective functions, constraints and decision variables. The second phase is multi-objective optimization of the formulated objectives using the available decision variables and taking into account the formulated constraints. Next, the decision makers have to decide how the various objectives are weighted, possibly using the methods part of the interactive decision support tool presented in this research, to select the best compromise solutions. This also means that the last phase will be the phase in which the involved parties have to negotiate about the compensation principle. However, in this case the consequences of a certain decision can be quantified directly.

Incorporation of externalities as objectives and a changing process of the determination of a DTM strategy also has implications for the traffic managers and traffic engineers on a tactical level, which have to translate the strategies into measures, procedures and algorithms. This translation will be a bigger challenge than in the current situation, because the traffic managers and engineers have to consider the multiple objectives and the agreed compensation principle. This means for example that the determination of triggers to start certain procedures or algorithms of traffic actuated control to be able to adapt to day-to-day variability, but also the monitoring and evaluation, becomes more complex.

The Almelo case in this research showed that there is not a single strategy that is optimal for all formulated objectives. This means that, although in policy documents often the simultaneous optimization of all objectives is formulated, policy makers have to decide which compensation principle to use for DTM policies. This research provides insights to make such decisions possibly in advance. In practice, the main opposed objectives can be chosen to determine the priorities of the policy makers. However, it is also possible to conclude that DTM policies should not focus on all objectives related to externalities, but for example on efficiency and emissions.

The cases showed that avoiding congestion, which is good for efficiency, is also good for air quality and climate. However, this does not mean that optimizing efficiency on a local level is also good for these externalities, because for these externalities it is for example better to avoid traffic using urban roads, while for efficiency the optimal use of full capacity (urban roads as well) will lead to improvements. Focusing on solving a local (urban) congestion problem can therefore deteriorate air quality and climate. In addition, lowering the speed limits at highways results in an improvement in externalities at this specific location, but is not necessarily the best deployment of this VSL to reduce emissions on a network level because of route choice effects. Neglecting behavioral responses when assessing the effects of measures before implementation can therefore result in erroneous decisions.

Traffic dynamics are an important explanatory variable for externalities. However, in practice often the outcome of STA models are used to calculate emissions. The deficiencies of these types of models have been addressed in this research, which also was an important reason to use a DTA model. When specific DTM strategies are deployed, in which for example traffic is metered at certain locations, the errors made in calculating emissions based on the outcome of STA models can be even larger. This implicates that the use of STA should be reconsidered for the assessment of externalities in current practice.

The measures considered in this research are DTM measures. However, it can be expected, based on the results of this research, that spatial planning and infrastructure planning can reduce externalities considerably. The relations found in this research can also be used to determine which measures related to spatial planning and infrastructural planning can reduce externalities but also how these can support DTM strategies. It may for example be better to avoid new housing projects between two close to each other urbanized areas to be able to meter and buffer traffic in between improving air quality in both urbanized areas.

8.3 Further research

Based on the findings, future research directions are suggested in previous chapters, which will be recapitulated in this section. Additionally, future research directions can be formulated from the wider perspective on the topic of this thesis. These directions are grouped the same way as the conclusions in the previous section.

Modeling framework

To assess externalities suitable methods have been found and applied for noise, climate and air quality. However, for traffic safety there is still a gap in knowledge to assess the effects taking into account the influence of traffic dynamics. It is known that speed and speed differences are important factors for traffic safety in terms of risk and severity of accidents. However, because of lack of data but also the focus in safety research, there is still no clear understanding about the effects of different traffic flow characteristics on safety. Future research is therefore needed for the assessment of traffic safety. Promising directions are the development of APMs per road type or a traffic situation based safety model in which risk figures are available per road type per traffic state. The latter one is a new type of safety model and in accordance with the suitable methods for emission models (sound and substances). However, the lack of data remains an important issue, especially because the occurrence of accidents decrease (i.e. safety has been significantly improved the last decades), but also because at least in the Netherlands the registration degree of accidents is decreasing. On the other hand, there is an enormous increase in available traffic data also for urban roads. This provides the opportunity to improve the understanding of the effects of different flow characteristics on safety.

Although suitable methods were found for noise, climate and air quality, the focus in research on assessment methods for these externalities is on STA and to some extent on microscopic DTA models. As a result not many external effect models are suitable to use in conjunction with macroscopic DTA models. In addition, traffic modeling and externality modeling are almost two separate worlds, which means that there is lack in understanding each others deficiencies and therefore suitability of using a certain externality model in conjunction with a traffic model. In addition, the legislation related to externalities (e.g. limit values) influence the development of external effect models and the connection with traffic models, which also affects research in which the relation between traffic and externalities is investigated. The interconnection between DTA models and external effect models should be more balanced dependent on the accuracy of the output of the DTA model and the needed accuracy of the input of the emission model. This also means that further research is needed to validate the connection between the externality models and DTA models, also for the framework presented in this research. In addition, the DTA and emission models should also incorporate the variables' distributions to be able to evaluate the significance of effects found. Research should be more focused on this interconnection and the incorporation of variables' distributions.

Next to the assessments of externalities used in this research, the knowledge about the adverse effects of traffic is increasing. Recently, it has for example been acknowledged that soot (part of particulate matter) is probably more important for public health than PM_{10} or $PM_{2.5}$ and that nitrogen deposition is important for the adverse effects on ecological environments. Especially soot, of which traffic can be locally the dominant source, will be of interest, because as a result the effects of the deployment of DTM on the concentrations will also be larger. In addition, a lot will change for modeling externalities as a result of the expected increase in alternative fuel vehicles. Hybrid, electric and hydrogen cars will change the relation between traffic dynamics and emissions significantly in the future.

Within this research only the emissions of substances and sound have been taken into consideration. However, for noise as well as air quality the number of people affected by high concentrations and high sound power levels are of interest. For air quality, dispersion models are used to determine the concentrations, while for noise, propagation models are used to determine the sound power levels at the facades. Although there is a strong correlation between emissions and concentrations or sound power levels, it can be of interest to extend the framework used in this research with dispersion and propagation models as well as to take the number of people affected into account.

The behavioral response taken into account is limited to route choice, because it is expected that this will be the main response. However other responses like destination choice, mode choice and especially departure time choice can be behavioral responses as well, dependent on the impact of a certain deployment of DTM measures on the utilities. Extending the framework taking into account these behavioral responses is therefore of interest, especially when also extreme strategies (e.g. total blockage of certain roads) are taken into consideration. However, considering these responses as well, will increase computation times significantly and as a result the scalability of the approach.

In addition, route choice behavior is modeled by assuming people will behave according to Wardrop's first principle of equilibrium wherein no driver can unilaterally change routes to improve his/her travel time. In this research a stochastic dynamic UE problem is solved when assessing the effects of implementing a certain deployment of DTM measures, which means no driver can unilaterally change routes to improve his/her perceived travel times. Although it is assumed that the strategies will be implemented for a longer period of time, in which road users can learn and adapt their route choice, in reality a true UE will not be reached because of various reasons like habitual behavior, day-to-day variability and the extent in which road users have exact knowledge of their alternatives. Another issue related to solving the dynamic UE problem is that the solution is not unique, meaning that there exist multiple equilibriums, which can be especially of interest also in practice when changing a strategy. Further research on understanding route choice behavior (e.g. when do road users start to reconsider their choice of route) and modeling of dynamic route choice is therefore needed. The day-to-day variability and the occurrences of incidents will also influence the robustness of the strategies in terms of the sensitivity in objective outcomes. Incorporation of robustness is therefore an interesting research direction as well, especially for the decision making process to choose the best compromise solution.

The DTM measures are modeled in a simplified way using link characteristics. For traffic signals additional assumptions have been made to be able to define the settings on an interval scale. However, in reality it is possible to influence traffic changing the capacity given at a certain direction. In addition, it is assumed that the settings of the DTM measure can change using fixed time intervals. Incorporating smaller or dynamic time intervals and extending the decision variables especially for traffic signals will provide more detailed strategies and possibly also further possible improvements for the externalities. Concerning the DTM measures, it also assumed that the available DTM measures to optimize the externalities are known in advance. However, it can be of interest to determine which DTM measures should be added or could be removed in a network to optimize the objectives even further.

Although in this research only control measures are considered, it is assumed that road users will comply with the deployment of these measures. Even when road users can experience the possible benefits of such deployment, it is not necessarily true that all road users comply and often enforcement measures are needed. When optimizing network performance, it is possible that the objectives, which the road management authorities are aiming at, are invisible for road users. This invisibility will increase even more when externalities are considered, because the road users themselves do not experience the benefits. Therefore, research is needed on how road users react on the objectives that are invisible to them and how enforcement and communication can be used to increase compliance. This also means that incorporating compliance in the assessment of strategies is of interest. In addition, there is an enormous increase in developments on ITS related to in-car devices, vehicle-to-infrastructure and vehicle-to-vehicle communications. These types of measures can contribute to the objectives related to externalities as well, but also on the compliance and communication to road users.

Solution approach
The framework and solution approaches presented in this research can be applied for other realistic cases as well. However, the scalability remains an issue, because an increase in decision variables and larger networks will increase the needed computation times to assess the effects of implementing a certain strategy. Extending the framework with the above mentioned possible additions will increase computation times even more. In this research, some procedures for acceleration have been proposed and also tested. Distributing the computations and using RSM methods can decrease needed computation times significantly. Using parallel computing means that the total computation time mainly depends on the needed computation time for solving the lower level problem and the number of generations. Improving computation times can be found in the solution approach of the upper level optimization problem as well as the lower level optimization problem. There is for example an enormous increase in developed heuristics to solve multi-objective optimization problems also in the field of EA (e.g. swarm intelligence) that should be investigated for this optimization problem. To be able to reduce computation times for the lower level problem there are also some interesting developments like marginal computing and quasi dynamic modeling (e.g. static assignment with queuing (STAQ)), which should be investigated further.

Although the approach presented in this research can be used for other cases as well and additional research on possible accelerations can improve the scalability, it is of interest to reduce the feasible set in advance or to choose a seeded starting population. Knowledge obtained by this research, extended with more cases and expert judgment can be used for this purpose. This knowledge can be used to combine settings of DTM measures in advance or reduce the possible settings and to formulate the seeded starting population.

Decision support
In this research a possible general framework for an interactive decision support tool is presented, but not explicitly tested. Further research is needed how the decision making process in which the best compromise strategy is chosen, can be supported. Using this framework in an actual decision making process can improve the framework, because then knowledge can be obtained about the needed information by the decision makers and the way it is used.

CBA is often used as an appraisal method for investments in traffic and transport to rank the solutions. This research showed that travel time losses are dominant when this method is used for weighting the objectives considered in this research. This means that if this economic principle with general accepted monetary values is used, it suffices to optimize efficiency to optimize the externalities as well. However, there is a lot of discussion about the CBA method and the monetary values used within this method. It is mainly used because it is assumed to be the best objective way to weigh the various effects. In practice, it is also shown that in many investments decisions in traffic and transport, the decision makers did decide to invest in a certain solution although the cost were higher than the benefits. This means that not only the economic value but also other criteria or implicitly other weightings are of importance for decision makers. Further research on monetary values, but also suitable ranking methods to support the decision making process in choosing the best compromise solutions for the deployment of DTM measures is needed.

Application
The applications presented in this research provided insights in the relations between the objectives and a general strategy that can be used in practice to reduce externalities. However, it is necessary to extend the number of cases to find out if similar strategies are found as in this research. This way it may become possible to derive more specific general strategies given the characteristics of supply and demand, which can be used by traffic engineers in practice without needing to solve a dynamic MO NDP. In addition, testing these strategies in real life by field operational tests is of importance to determine if the expected behavioral responses are also found in practice.

Within this research network performance measures have been chosen to assess the effects on externalities as well as efficiency, assuming cooperating road management authorities. However, in practice there are more road management authorities involved with each having their own objectives and measures available. Earlier research already has proven that cooperation will result in improvement in total efficiency and it can be expected that this is also the case for the objectives related to externalities. In practice, it also has been acknowledged that road management authorities should cooperate and cooperation also increased. However, it can also mean that although there is net decrease of externalities, certain road management authorities will be confronted with an increase in problems, while others will mainly benefit. As a result this can result in choosing sub-optimal solutions unless there are suitable ways to compensate between the road management authorities. Research on the consequences for the various road management authorities as well as possibilities to compensate are therefore of interest.

In addition, the objective functions formulated in this research are network performance measures, in which for noise and air pollutions weights are used to take into account that high concentrations in residential areas are more harmful than high concentrations in rural areas. These weighting factors have been chosen in a pragmatic way and in future research using realistic cases can be further improved based on the number of people living near the roads and distances between roads and houses. In addition, in practice it can become relevant to take into account additional outcome constraints for example related to the formulated limit values. By taking these constraints into account other strategies can prevail that do not necessarily reduce the impacts of traffic on externalities in an optimal way (e.g. because existing background concentrations influence the feasibility of solutions).

The number of trucks but also the current changes in car park (i.e. increase in alternative fueled cars) can have a significant impact on the relations found in this research. Especially because it is expected that the transport of goods will increase, the impact of traffic dynamics on externalities will change as a result of the alternative fueled cars and the expected re-urbanization and decrease of car ownership. Further research on the influence of these aspects is an interesting research direction, as well as differentiated strategies for vehicle classes and possible DTM measures to be able to differentiate between them.

Next to the earlier mentioned combination of spatial planning, infrastructure planning and deployment of DTM strategies to reduce externalities, this research also provides some insights for traffic nuisance during road works, which is especially in the Netherlands part of the procurement process. Further research on this subject as well as strategies for other non-recurrent traffic situations like incidents is a challenging research direction, also because of the earlier mentioned needed knowledge on behavioral responses of road users.

This research provided a suitable approach to incorporate externalities as objectives for dynamic traffic management on a network level, taking route choice effects and traffic dynamics into account. Scalability remains an issue, although possible methods are presented to improve the scalability of the approach. Based on test cases, insights have been obtained on DTM strategies to optimize the objectives on a network level. Recommendations for further research are presented in this section of which the behavioral response and the understanding of the decision making process will probably be most important to realize successful sustainable dynamic traffic management.

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Notations

List of symbols and notations

Framework:

z	objective vector
z_i	objective function connected to objective *i*
z_i^N	normalized value objective function, objective *i*
$\tilde{z}_i$	approximated objective function connected to objective *i*
z_i^*	objective value optimal solution of objective *i*
z^*	ideal objective vector
$z^\wedge$	vector containing upper bounds of objectives
I	total number of objectives
q	link flows
q_c	capacity per lane
q_o	outflow capacity
q_{ao}	outflow capacity link *a*
q_{ac}	capacity of link *a* per lane
q'_{ac}	corrected capacity of link a as a result of lane configuration
$q_{am}(t)$	vehicle type *m* inflow to link *a* at time *t* (veh)
v	link speeds
v_f	free flow speed
v_c	speed at capacity
$v_{am}(t)$	average speed of vehicle type *m* on link *a* at time *t* (km/h)
v_m^{ref}	reference speed dependent on vehicle type *m*, for noise calculations
k	link densities
k_c	critical density
k_j	jam density
$k_{am}(t)$	average density of vehicle type *m* on link *a* at time *t* (km/h)
V	flow (veh/time period)
G	network, directed graph
N	nodes
A	links (Arcs)
a	index of a link
C	link characteristics
C_a	characteristics of link *a*
$C_a(S^t)$	characteristics of link *a* as a result of the combined application of available DTM measures during time interval *t*
C_{a0}	characteristics of link *a* without any DTM measures
CT	cycle time traffic signal
g_a	effective green time given to link *a*
g_a^p	percentage of green time given to link *a*
l	number of lanes
l_s	total number of dedicated turning lanes
l_m	number of lanes dedicated for the major flow
D	dynamic travel demand
F	feasible set of solutions

$\underline{F}$	feasible set of solutions for static version of optimization problem
$\tilde{F}$	restricted feasible set of solutions
S	solution, set of applications of strategic DTM measures
S_j	solution j
S^t	settings of available DTM measures in time interval t
s_b^t	setting of measure b in time interval t
$\underline{s}_b$	setting of measure b in static version of optimization problem
S_i^*	optimal solution for objective i
$S_i^{\wedge}$	worst performing solution for objective i
S'_j	solution part of set X'
S_j^*	Pareto optimal solution part of X^*
$\underline{S}_i^*$	optimal solution for objective i for the static version of the SO NDP
X	set of all possible sets of solutions
$\hat{X}$	set representing extremal individuals
X'	a set of solutions
$\hat{X}'$	a combination of a set of solutions X' with the set of extremal individuals $\hat{X}$
X^*	Pareto optimal set of solutions
$\tilde{X}^*$	approximated Pareto optimal set of solutions
x	explanatory variable
B	total number of different DTM measures
b	index of a DTM measure
M_b	number of different possible settings for DTM measure b
Γ^{DTA}	dynamic user equilibrium problem
d	road type
m	vehicle type
R	injury accident risk
R_d	injury accident risk of vehicle type m for road type d (injury accidents/(veh*km))
E	emission factor
$E_{md}^{CO2}(\cdot)$	CO_2 emission factor of vehicle type m, depending on average speed (grams/(veh*km))
$E_{md}^{NO_x}(\cdot)$	emission factor of NO_x of vehicle type m on road type d, depending on average speed (grams/(veh*km))
$L_{am}(\cdot)$	average sound power level for vehicle type m, on link a depending on the average speed (dB(A))
$\bar{L}_w$	weighted average sound power level on network part with urbanization level w (dB(A))
ℓ_a	length of link a (km)
δ_{ad}^R	safety road type indicator, equals 1 if link a is of road type d, and 0 otherwise
δ_{ad}^E	emission road type indicator, equals 1 if link a is of road type d, and 0 otherwise
δ_{aw}	urbanization level indicator, equals 1 if link a has urbanization level w, and 0 otherwise
η_w	correction factor for urbanization level w (dB(A)))
w_a	level of urbanization around link a
α_m, β_m	parameters dependent on vehicle category for noise calculations
Δt	time interval output data DTA model
T	total assessed time period
α_a	correction factor for dedicated turning lanes
β	correction factor for total lost time
γ	percentage of capacity used of minor dedicated turning lanes during the green time
e	VSL value, ratio of adjusted speed limit by VSL and the basic speed limit

Solution approach:

H	maximum number of generations
h	generation
OU_0	initial population SPEA2+ algorithm
OU_h	archive generation *h* in which truncation is done using distances in objective space
P	parents
P_h	parents generation *h*
Q	children
Q_h	children generation *h*
U	archive
U_0	initial population
U_h	archive generation *h*
DU_h	archive generation *h* in which truncation is done using distances in solution space
W	total number of solutions
W_p	population size
W_u	archive size
Y_h	combined set of solutions of archive U_h and children Q_h generation *h*
ρ_{rec}	recombination rate, percentage of selected parents that are recombined
ρ_{mut}	mutation rate, percentages of genes selected that will be mutated
ρ_{mut}^{init}	initial mutation rate
$SMO(X')$	spacing metric value in objective space of set X'
$SMS(X')$	spacing metric value in solution space of set X'
$DMO(\hat{X}')$	diversity metric value in objective space of set X'
$CTS(X', X'')$	value of coverage of two sets, level in which the solutions X' weakly dominates X''
$NONDOM(X', X'')$	value of domination, extent in which solutions X'' are equal or worse than X'
$EPS(X', X'')$	result of binary epsilon indicator, the minimum factor epsilon such that any of the solutions X'' is dominated by at least one of the solutions X'
$SSC(X')$	size of the space covered by solutions X' in objective space
$CDTS(X', X'')$	size of the space coverage difference by solutions X' and X'' in objective space
$CDTS_{rel}(X', X'')$	size of the space coverage difference by solutions X' and X'' in objective space
δ	distance
δ_w	Euclidean distance between each solution and its nearest solution
$\bar{\delta}$	average of δ_w
ξ	additional number of solutions as a result of combining X' with $\hat{X}$
Ψ	approximation set needed to form the training set
Φ	training set for estimating surrogate model
χ_j	parameters surrogate model
$\underline{SO\ NDP}_i$	static version of the single objective network design problem, considering objective *i*
$SO\ NDP_i$	original version of the single objective network design problem, considering objective *i*
ε	parameter

Pruning and ranking:

$Trade-off$	trade-off between two objectives for two solutions
AHP	analytical hierarchy process score
AHP_{rev}	revised analytical hierarchy process score
WSM	weighted sum method score
WPM	weighted product method score
WAR	weighted average rank score
c_i	concordance parameter objective i
CI	credibility index
Λ	concordance index
Δ^1	insignificance parameter PIT-filter
Δ^2	parameter PIT-filter, minimum level of spread along the Pareto front
d_i	disconcordance index objective i
$\Theta(j)$	silhouette width of cluster j
ω_i	indifference threshold for objective i
ρ_i	preference threshold for objective i
υ_i	veto threshold for objective i
θ_i	relative weighting factors ranking methods
θ_i^M	monetary values per objective
$\Upsilon_i(S_j)$	rank of solution j for objective i

List of abbreviations

ADT or AADT	(annual) average daily traffic
AHP	analytical hierarchy process
APM	accident prediction model
ARBM	accident risk based model
ARTEMIS	assessment and reliability of transport emission models and inventory systems
AR-INTERIM-CM	adaption and revision of interim computation methods
CAR	calculation of air pollution from road traffic
CBA	cost benefit analysis
CNDP	continuous network design problem
CPM	crash prediction model
DBMO-SA	dominance based multi-objective simulated annealing
DNDP	discrete network design problem
DNL	dynamic network loading
DTA	dynamic traffic assignment
DTM	dynamic traffic management
DUE	dynamic user equilibrium
EMOA	evolutionary multi-objective algorithms
EA	evolutionary algorithm
ELECTRE III	elimination et choix traduisant la realité III
EU	European Union
FA	function approximation
GA	genetic algorithm
HCM	highway capacity manual
HGV	heavy good vehicle
ITS	intelligent transport systems
LHS	latin hypercube sample
MCDM	multi-criteria decision making
METANET	modèle d'ecoulement du traffic autoroutier network
MNDP	mixed network design problem
MOGA	multi-objective genetic algorithm
MO NDP	multi-objective network design problem
MPEC	mathematical problem with equilibrium constraints
NDP	network design problem
NP-hard	non-deterministic polynomial-time hard
NSGA-II	non-dominated sorting genetic algorithm II
PCE	potential crash energy
PET	post encroachment time
PIT	practically insignificant trade-off
PROMETHEE	preference ranking organization method for enrichment evaluations
VMS	variable message sign
VSL	variable speed limit
RMV	reken- en meetvoorschrift
RSM	response surface methods
WAR	weighted average ranking
WPM	weighted product method
WSM	weighted sum method
SO NDP	single-objective network design problem
SPEA2	strength Pareto evolutionary algorithm 2
SPEA2+	strength Pareto evolutionary algorithm 2+
SPI	safety performance indicator
SPF	safety performance function
STA	static traffic assignment
TTC	time to collision
UE	user equilibrium

Summary

Mobility is an important prerequisite for economic growth. Due to the increasing demand and difficulties to match supply, congestion is part of daily traffic. Next to accessibility problems, traffic is also responsible for livability problems. These unwanted side-effects of traffic, called externalities, are of increasing importance when decisions are made in the field of traffic and transport and the cost of these externalities have become substantial. The challenge has become to manage mobility in such a way that locations stay accessible and externalities are minimized. Policy documents are therefore also aiming at facilitating mobility growth and reducing externalities. Because there is a strong spatial correlation between problems and strong spatial correlation between the effects of traffic measures, these should be considered on a network level. Dynamic traffic management (DTM) measures can be deployed to improve the utilization of networks. Traffic dynamics are important explanatory variables for accessibility and externalities and DTM measures can be used to influence these traffic dynamics locally or on a network level e.g. by influencing route choice behavior. In research and practice it has already been proven that on a local or corridor level DTM measures can be used to reduce externalities. However, there has been a strong focus on the deployment of DTM measures on operational and tactical level in which the behavioral responses have not been taken into account. Current practice is that the strategic level is mainly concerned with the evaluation of a few or sometimes even one predefined strategy. When externalities are considered in these strategies, these are often implicitly taken into account as a constraint rather than an objective. Optimization of accessibility as well as externalities introduces a new challenge. Objectives can be conflicting, which means that there probably does not exist one solution that optimizes al objectives simultaneously. To be able to choose a single strategy for actual implementation, decision makers need to determine how the objectives should be weighted. However, choosing such compensation principle may be difficult in advance without knowing how the objectives relate and what the consequences are of a certain decision. This type of knowledge is currently lacking and not earlier research has been done on how these objectives relate and can be optimized taking traffic dynamics and route choice behavior of road users into account. The objective of this research is to provide a suitable approach to optimize these multiple objectives using DTM measures on a network level taking behavioral responses into account to be able to provide insights in how to deploy these measures.

This optimization problem is a specific example of a multi-objective network design problem (MO NDP), often modeled as a bi-level optimization problem. At the upper level, objectives of road management authorities related to accessibility and externalities are being optimized, using DTM measures as decision variables. At the lower level, road users optimize their own objectives, generally travel time or travel cost. Both levels are interdependent, because road management authorities determine the settings of the DTM measures based on the behavior of road users, and road users adapt their behavior based on the settings of the DTM measures. This interaction results in a difficult (NP-hard) optimization problem, identified as one of the most complex optimization problems in traffic and transport to solve, for which often heuristics are used. To assess the performance of a possible deployment of DTM measures (i.e. a solution) the output of a transport model can be used. In almost all earlier research on NDP, static traffic assignment models were used. However, to be able to take traffic dynamics

into account, relevant for the deployment of DTM measures as well as for the effects on externalities, a dynamic traffic assignment (DTA) model is more suitable. The introduction of a DTA model increases complexity, because of the needed computation times, but also since it requires suitable methods to assess the impact of a solution on externalities. Solving a MO NDP instead of a single objective (SO) NDP in which several objectives are combined in one single objective function, results in a Pareto optimal set of solutions. This set contains valuable information to provide insights in how to deploy DTM measures to improve accessibility and externalities. This Pareto optimal set can also be used within the decision making process, to support decision makers to learn about the problem and solutions before choosing a strategy to implement.

In this research a suitable framework has been developed for the multi-objective optimization of traffic systems in which accessibility and externalities are the objectives and DTM measures are the decision variables, in which modeling of externalities using DTA models was the main challenge. This dynamic MO NDP has been formulated as a bi-level optimization problem in which in the lower level a dynamic user equilibrium (DUE) problem is solved using the Streamline macroscopic DTA model assuming fixed demand. Secondly, solution approaches have been developed, compared and tested to solve this MO NDP. Thirdly, methods to support decision makers using an interactive decision support tool have been applied to show the advantages and disadvantages of these methods. Finally, the approach is applied in test cases to provide insights on the consequences of incorporation of externalities as objectives for the deployment of DTM measures.

Objective functions
The system objectives are formulated as network performance measures to reduce complexity, resulting in one single objective function per externality and one for accessibility. For accessibility, efficiency is optimized by minimizing total travel times. For climate the minimization of total CO_2 emissions and for traffic safety the minimization of total number of injury accidents is used as objective functions. Minimizing the weighted sound power level is used for noise and for air quality minimizing the weighted sum of NO_x (or PM_{10}). The weights depend on the level of urbanization, because for these objectives the location where the substances or sound is emitted is of interest. To calculate the objective functions the DTA model used to solve the lower level optimization problem, is connected with effect models. The interconnection between DTA models and external effect models should be balanced depending on the accuracy of the output of the DTA model and the needed accuracy of the input of these models. Based on the models and research available, it is found that for traffic safety there is still a gap in knowledge to assess traffic safety based on the output of DTA models. It would be recommendable to use accident prediction models (APMs) incorporating traffic dynamics as explanatory variables in conjunction with macroscopic DTA models. However, because there does not exist a complete set of APMs covering all road types, incorporating traffic dynamics as well, a risk based model is used in this research to assess traffic safety. For modeling emissions traffic situation based models are most suitable for macroscopic DTA models and therefore the ARTEMIS emission model is used in this research. Although relatively little research is done in assessing noise in conjunction with DTA models, the methods available to determine the source emissions are suitable. Often source emission models use a correction factor for accelerations. Uncertainties in estimating individual accelerations and decelerations based on the outcome of macroscopic DTA models are probably higher than the impact of accelerations and decelerations on sound power level. The AR-INTERIM-CM noise model does include the average impact of accelerations in the emission function (separate emission functions and therefore traffic situation based). In this

research two methods are used; the RMV noise model without taking the effect of accelerations and decelerations into account and the AR-INTERIM-CM noise model, which does.

Decision variables
Only traffic control measures are considered that can actually influence supply of infrastructure and these are modeled in a simplified and efficient way by using link characteristics to reduce the decision variables. These link characteristics include the capacity, outflow capacity, number of lanes, free speed, speed at capacity and jam density, and are captured in a fundamental diagram.

Solution approach
Genetic algorithms (GA) have been proven to be capable of solving SO NDP as well as MO NDP, NDP in which DTM measures are the decision variables and NDP in which externalities are the objectives. Out of the many multi-objective GAs that have been proposed earlier, three algorithms that have proven to provide excellent results (i.e. strength Pareto evolutionary algorithm 2 (SPEA2), the non-dominated sorting genetic algorithm II (NSGA-II) and strength Pareto evolutionary algorithm 2+ (SPEA2+)) have been selected. Their performance was compared for the dynamic MO NDP in this research. The results indicate that the SPEA2 and mainly the SPEA2+ approach are able to obtain a more diverse solution set in the objective space as well as in the solution space than the NSGAII approach. However, the NSGAII and SPEA2+ approach perform similar in attaining the global trade-offs and both perform better than SPEA2. All heuristics do require a large number of function evaluations. Every function evaluation requires solving the DUE problem by the DTA model, which is computationally expensive, especially in large scale applications. To relax these time-consuming optimization procedures, three algorithms that use response surface methods (RSM) to estimate a surrogate model are proposed and compared. All algorithms used the SPEA2+ algorithm as a basis. Comparison of the algorithms given a fixed computation time budget shows that the use of RSM methods does not result in missing relevant parts of the Pareto optimal set. The average performance of the algorithms is similar and the development over generations of the performance measures shows that all three algorithms using RSM methods accelerate the search at the start considerably. However, the algorithms using these RSM methods tend to converge faster, possibly to a local optimum and therefore loose their head start, because these algorithms depend largely on the quality of the surrogate model. Because computation times are important for solving the MO NDP, the algorithms using RSM methods are of interest, especially for larger computationally expensive networks.

Decision support
To be able to choose between solutions a compensation principle is needed, which is a public policy decision. The Pareto optimal set contains valuable information to support this decision making process, which allows the decision makers to learn about the problems and solutions before choosing a certain strategy to implement. In addition, multi-objective optimization has the advantage of considering all possible strategies instead of evaluating a few predefined strategies. In this research an interactive decision support tool is proposed. Part of this tool are pruning and ranking methods. Pruning methods reduce the Pareto optimal set retaining distinctive solutions and therefore the main characteristics of the Pareto optimal set. Pruning may be useful to circumvent the possible difficulties in analyzing and comprehending the large Pareto optimal set in the decision making process. Three pruning methods are compared in this research, namely convex hull, clustering and practically insignificance trade-off (PIT) filter. Clustering can be used to analyze the main choices, but should not be used to select a

subset of solutions, because choosing a representative solutions for one cluster is not trivial. The convex hull filter can result in a significant reduction of the Pareto optimal set and is in accordance with ranking methods using linear weighting, but may result in neglecting interesting parts of the objective space. The PIT filter is the most suitable method to choose a subset, because it is related to the changes in trade-offs between solutions and therefore retains the interesting solutions for the decision making process.

Ranking methods are basically multi-criteria decision making (MCDM) methods that are used to select the best compromise solutions for closer investigation. Cost-benefit analysis (CBA), in which the effects are monetized, is an often used appraisal method within the field of traffic and transportation. Application of the CBA method shows that efficiency turns out to be the most dominant objective, which means that only objectives that are aligned with efficiency will profit to some extent when this method is used. If decision makers decide that economic trade-off should be the way to rank the solutions it can be stated that optimizing efficiency will result in the best compromise solution for externalities as well. However, the monetary values often used are debatable and if decision makers want to take externalities into account more seriously other ranking methods should be considered. In this research the elementary methods weighted sum method (WSM) and weighted product method (WPM) are applied as well as the often used analytical hierarchy process (AHP) and the elimination et choix traduisant la realité III (ELECTRE III) method. The main difference between the WSM, WPM and AHP ranking methods is the way the objectives are normalized, which obviously influences the outcomes and sensitivity levels for weighting factors. The ELECTRE III is a method which, in contrast to the WSM, WPM and AHP, can take uncertainties into account and is possibly a more suitable method to choose the single best compromise solution. However, this method is complex while the WSM or AHP method are more transparent and therefore more suitable to use in an interactive decision support tool.

Applications
To provide insights on how to deploy DTM measures to optimize externalities on a network level, the outcome of test cases using a synthetic network and a realistic network of the city of Almelo is used. Both cases show that the objectives efficiency, air quality and climate are aligned and are opposed to traffic safety and noise. However, there is not one single solution that optimizes all objectives simultaneously, which means there exist trade-offs between all five objectives. The optimal design for efficiency aims for avoiding congestion using full capacity of the available infrastructure. Avoiding congestion is also of importance for the emissions of substances. Because for air quality emissions in urbanized areas are weighted higher, the optimal design for air quality searches for the best trade-off between avoiding congestion and usage of the urban routes. In the synthetic case the objectives climate and efficiency turn out to be almost co-linear, which is less the case in the realistic case of the city of Almelo. Because in the synthetic case it is assumed that capacity increases when lowering the speed limit and lowering the speed limit also decreases emissions, the optimal designs for efficiency and climate are similar. In the realistic case of the city of Almelo the increase in capacity is not assumed and because of more road types and route choice options the optimal designs for climate and efficiency are less similar. The optimal designs in the realistic case of the city of Almelo shows that avoiding congestion is also good for air quality and climate. However, the optimal solutions for air quality and climate meters certain flows on specific locations to avoid detouring and congestion downstream, and to increase the use of the ring road, while the optimal solution for efficiency distributes delays more. For traffic safety the optimal design tries to maximize the use of safest routes (highway routes), and avoiding urban routes, which are less safe. For noise, the optimal design when using the RMV noise model

aims at lowering speeds as much as possible and avoiding traffic using the urban routes. However, when the increase of propulsion noise in saturated traffic conditions is taken into account, using the AR-INTERIM-CM noise model, the optimal design for noise still aims at lowering speeds, but avoiding congestion mainly on urban roads as well. In the latter case noise is therefore less opposed to efficiency than if this effect is not reckoned with. Using cluster analysis the Pareto optimal set was further analyzed also for parts of the network. Results show that the differences between the clusters are coherent on average and there is also a strong correlation between the distances between solutions in objective space and their distances in solution space. However, solutions can still be distinct while resulting in similar performance in objective space, which means additional criteria like equity and complexity can be used to choose the best compromise solution.

The cases in this research showed that there is not one single solution that optimizes all objectives simultaneously. However, given the relations between the objectives it is possible to formulate a general strategy that can be used in many cases in practice to reduce externalities. Because highways are often situated in less urbanized area's and are the relative safest roads, a general strategy could be to facilitate traffic on higher order roads possibly decreasing the speed limit and metering and buffering vehicles at smart locations (often at the borders of the urbanized areas), while facilitating traffic in the city avoiding congestion. The metering of traffic should be used to avoid congestion in urban area's and to influence route choice of traffic in such a way mainly the higher order roads are used. However, where traffic should be exactly metered and buffered and to what extent depends on the routes available, spatial planning and demand in the specific case and can therefore be complex to determine in practice.

Implications and further research
The results can be translated in implications for various aspects in the field of traffic and transport. When embracing an actual optimization of objectives, the current process of formulating DTM strategies, like the STM process, would become less expert judgement based. Also, the translation of the DTM strategies into measures, procedures and algorithms on tactical level will become a bigger challenge, because complexity increases to determine for example triggers. In addition, policy decisions will be needed concerning the compensation principle. Next, the cases showed that the behavioral response of route choice is important to take into account. Focusing on reducing externalities on a local level, could result in a deteriorating situation on network level. Another implication is that if DTM strategies are used to reduce externalities, in which metering of traffic can be one of the possible measures, the current use of static traffic assignments models for the assessment of externalities should be reconsidered. Finally, using DTM strategies may have implications for spatial planning and infrastructural planning to support these strategies.

Based on the findings, further research directions can be formulated. For the modeling framework, the assessment of traffic safety should be further improved incorporating traffic dynamics. Further research is also needed on the interconnection of transport models and externality models and its validation. Knowledge of the adverse effects of traffic is increasing, as well as changes in these effects as a result of alternative fueled vehicles. These will influence the modeling framework used in this research. In addition, several extensions of the presented modeling framework are possible, incorporating for example additional and improved behavioral responses, robustness and more detailed DTM modeling. For the solutions approach the computation times remain an issue. Further research is needed to reduce the time needed to solve the upper level as well as the lower level problem. For decision support it is of interest to investigate what information is needed by the decision makers and the way it is used. In addition, further research will be needed to determine a suitable multi criteria decision making method when incorporating externalities as objectives. The application of the presented framework should be further extended, also in practice, to extent knowledge on the incorporation of externalities as objectives. This is of importance to derive specific general strategies, but also to understand what the consequences are for the various road management authorities, what the consequences are if more detailed objectives and constraints are used or differentiated strategies are used for vehicle classes. In addition, further research on incorporating externalities as objectives for other types of decision variables (i.e. measures) or nonrecurrent traffic situations are of interest as well.

Final remarks
This research provides a suitable approach to incorporate externalities as objectives for dynamic traffic management on a network level taking route choice effects and traffic dynamics into account. Scalability remains an issue, although possible methods are presented to improve the scalability of the approach. Based on test cases insights have been obtained on DTM strategies to optimize the objectives on a network level. The results of this research have implications for the deployment of DTM measures and DTM policies. Recommendations for further research have been presented in which the behavioral response and the understanding of the decision making process will be important to realize successful sustainable dynamic traffic management.

Samenvatting

Mobiliteit is een belangrijke vereiste voor economische groei. Als gevolg van de toenemende verkeersvraag en niet altijd overeenkomstige aanbod van infrastructuur treden files en bereikbaarheidsproblemen dagelijks op. Naast voor bereikbaarheidsproblemen is verkeer ook verantwoordelijk voor leefbaarheidsproblemen. Deze ongewenste neveneffecten, ook wel externe effecten genoemd, van verkeer spelen in toenemende mate een rol in de besluitvorming op gebied van verkeer en vervoer. De kosten van deze externe effecten zijn bovendien substantieel. Het verkeer- en vervoerbeleid richt zich dan ook op het zo goed mogelijk faciliteren van de mobiliteitsgroei enerzijds en het reduceren van de externe effecten anderzijds. Aangezien er een sterke ruimtelijke correlatie bestaat tussen zowel de verkeersproblemen als de effecten van maatregelen, zouden deze op netwerkniveau moeten worden beschouwd. Dynamisch verkeersmanagement (DVM) maatregelen kunnen worden ingezet om verkeersnetwerken beter te benutten. De verkeersdynamiek is daarbij een belangrijke verklarende variabele voor zowel de bereikbaarheid als de externe effecten van verkeer. DVM-maatregelen kunnen deze verkeersdynamiek lokaal en op netwerkniveau, bijvoorbeeld door routekeuzegedrag, beïnvloeden. Onderzoek en praktijkervaring tonen aan dat DVM-maatregelen op lokaal niveau kunnen worden ingezet om de externe effecten te reduceren. Echter, de focus heeft voornamelijk gelegen op de inzet van deze maatregelen op operationeel en tactisch niveau zonder de gedragsreacties van weggebruikers mee te nemen. In de huidige praktijk wordt op het strategische niveau slechts een paar, en soms zelfs slechts één, vooraf gedefinieerde strategie geëvalueerd. Indien de externe effecten hierbij worden meegenomen dan is dit veelal als randvoorwaarde en niet als een doelstelling. Het optimaliseren van zowel de bereikbaarheid als de externe effecten van verkeer introduceert een nieuwe uitdaging. Deze doelstellingen kunnen namelijk conflicterend zijn, hetgeen betekent dat er waarschijnlijk niet één enkele strategie bestaat die alle doelstellingen tegelijkertijd optimaliseert. Om tot een te implementeren strategie te komen zullen beleidsmakers dan ook moeten vaststellen hoe de doelen onderling gewogen moeten worden. Echter, het vooraf kiezen van een dergelijk compensatieprincipe is moeilijk zonder kennis over hoe de doelen samenhangen en wat de consequenties zijn van een keuze hierin. Deze kennis ontbreekt en niet eerder is er onderzoek geweest naar de relaties tussen deze doelen en hoe deze doelen kunnen worden geoptimaliseerd, rekening houdend met de verkeersdynamiek en routekeuzegedrag van weggebruikers. Het doel van dit onderzoek was dan ook het ontwikkelen van een geschikte manier om deze verschillende doelstellingen te optimaliseren op netwerkniveau, rekening houdend met gedragsreacties, om uiteindelijk inzicht te bieden in hoe de inzet van DVM-maatregelen daaraan kan bijdragen.

Dit optimalisatieprobleem is een specifiek voorbeeld van een multi-criteria netwerk ontwerp probleem (MO NDP), welke meestal wordt geformuleerd als een bi-level optimalisatieprobleem. In het ‘upper level’ worden daarbij de doelstellingen van de wegbeheerders, gerelateerd aan bereikbaarheid en de externe effecten van verkeer, met behulp van DVM-maatregelen geoptimaliseerd. In het ‘lower level’ optimaliseren weggebruikers hun eigen doelen, welke over het algemeen gerelateerd zijn aan reistijd of reiskosten. Beide niveaus zijn daarbij onderling afhankelijk, want de wegbeheerders bepalen de inzet van de DVM-maatregelen afhankelijk van het gedrag van weggebruikers, terwijl weggebruikers hun gedrag aanpassen afhankelijk van de inzet van DVM-maatregelen. Deze interactie resulteert

in een lastig (NP-hard) optimalisatieprobleem welke is geïdentificeerd als één van de meest complexe optimalisatieproblemen binnen verkeer en vervoer en waarvoor vaak heuristieken worden gebruikt als oplossingsmethode. Om een bepaalde inzet van DVM-maatregelen (een oplossing) te evalueren kan een verkeersmodel worden gebruikt. In vrijwel al het eerdere onderzoek naar netwerkontwerpproblemen (NDP) zijn statische toedelingsmodellen gebruikt. Echter, om de verkeersdynamiek mee te kunnen nemen, welke relevant is voor de inzet van de DVM-maatregelen maar ook voor de bepaling van de externe effecten, is een dynamische toedeling (DTA) beter geschikt. De introductie van een DTA model vergroot echter de complexiteit vanwege de langere rekentijd en vanwege de geschiktheid van methoden om de impact van een oplossing op de externe effecten te kunnen bepalen.
Het oplossen van een MO NDP in plaats van een NDP met één enkele doelfunctie (SO NDP) waarin de verschillende doelstellingen worden gecombineerd, resulteert in een Pareto-optimale set van oplossingen. Deze set bevat waardevolle informatie over de inzet van DVM-maatregelen in relatie tot bereikbaarheid en de externe effecten van verkeer. Deze set kan ook worden gebruikt in de ondersteuning van beleidsmakers binnen het beslisproces, doordat deze set hen in staat stelt te leren over het probleem en mogelijke oplossingen, voordat een strategie wordt gekozen.

In dit onderzoek is een raamwerk ontwikkeld voor de multicriteria optimalisatie van verkeerssystemen, waarbij bereikbaarheid en externe effecten de doelen zijn en DVM-maatregelen de beslisvariabelen. Hierbij was het evalueren van de externe effecten van verkeer op basis van de uitkomsten van een DTA model de grootste uitdaging. Het MO NDP is geformuleerd als een bi-level optimalisatieprobleem waarbij het ‘lower level’ optimalisatieprobleem is opgelost door het berekenen van een dynamisch gebruikersevenwicht, gebruikmakend van het macroscopische DTA model Streamline en waarbij een vaste verkeersvraag is verondersteld. Ten tweede zijn oplossingsalgoritmen ontwikkeld, getest en vergeleken voor dit MO NDP. Ten derde zijn methoden ter ondersteuning van beleidsmakers in een interactief beslissingsondersteunend systeem toegepast om de voor- en nadelen in beeld te brengen. Ten slotte is de aanpak toegepast in testcases om inzicht te krijgen in de consequenties van het meenemen van de externe effecten van verkeer in de netwerkbrede inzet van DVM-maatregelen.

Doelfuncties
De systeemdoelen zijn in dit onderzoek geformuleerd als netwerkmaten om de complexiteit te reduceren, resulterend in één enkele doelfunctie per extern effect en één voor bereikbaarheid. Voor bereikbaarheid is de efficiëntie geoptimaliseerd door het minimaliseren van de totale reistijd. Voor klimaat is de totale CO_2-emissie en voor verkeersveiligheid is het totaal aantal letselongevallen gebruikt als doelfunctie. De gewogen gemiddelde geluidsemissie is gebruikt voor geluid en voor luchtkwaliteit is de totale gewogen som van NO_x (of PM_{10}) als doelfunctie gehanteerd. De toegekende gewichten zijn daarbij afhankelijk gesteld van de stedelijkheidsgraad, aangezien voor deze laatste twee doelstellingen de locatie waar het geluid of de stoffen worden uitgestoten van belang zijn. Om de doelfuncties uit te rekenen is het DTA model gekoppeld met een aantal effectmodellen. De koppeling tussen dergelijke modellen dient een balans te zijn tussen de gevraagde nauwkeurigheid van het effectmodel en de nauwkeurigheid van de uitkomsten van het verkeersmodel. Uit de beschikbare modellen en literatuur blijkt dat de kennis ontbreekt om verkeersveiligheid te evalueren op basis van de output van DTA modellen. Ongevalspredictiemodellen (APM’s) die verkeersdynamiek meenemen als verklarende variabele zijn in potentie het meest geschikt. Er bestaat echter nog geen complete set van APM’s voor alle wegtypen waarbij dit het geval is. Daarom is een methode op basis van risicocijfers gebruikt in dit onderzoek. Voor het modelleren van de

emissies van stoffen is het gebruik van verkeerssituatieafhankelijke emissiemodellen in combinatie met DTA modellen het meest geschikt. In dit onderzoek is daarom het emissiemodel ARTEMIS gebruikt voor de emissies van stoffen (CO_2, NO_x en PM_{10}). Ondanks dat er beperkt onderzoek is gedaan naar de evaluatie van geluid in combinatie met DTA modellen, zijn de beschikbare modellen bruikbaar. In de meeste gevallen worden in deze emissiemodellen correctiefactoren gebruikt voor acceleraties. De onzekerheid in het schatten van de individuele acceleraties en deceleraties van voertuigen op basis van deze DTA modellen is echter waarschijnlijk groter dan de impact hiervan op de geluidsemissie. Het geluidsmodel AR-INTERIM-CM neemt de gemiddelde impact van acceleraties wel direct mee in de emissiefuncties middels gescheiden emissiefuncties voor vrije doorstroming en file. In dit onderzoek zijn daarom twee methoden gebruikt; het geluidsmodel RMV zonder rekening te houden met het effect van acceleraties en deceleraties en het geluidsmodel AR-INTERIM-CM dat dit wel doet.

Beslisvariabelen
In dit onderzoek zijn enkel verkeersbeheersingsmaatregelen meegenomen welke daadwerkelijk het aanbod van infrastructuur kunnen beïnvloeden. Deze maatregelen zijn (om het aantal beslisvariabelen te reduceren) op een vereenvoudigde en efficiënte manier gemodelleerd door gebruik te maken van de linkkarakteristieken. Deze linkkarakteristieken bevatten de capaciteit, uitstroomcapaciteit, aantal rijstroken, vrije snelheid, snelheid bij capaciteit en de stremmingsdichtheid.

Oplossingsmethode
Genetische algoritmen (GA) hebben aangetoond geschikt te zijn voor het oplossen van SO NDP en MO NDP, voor NDP's waarin DVM-maatregelen de beslisvariabelen waren en voor NDP's waarin de externe effecten van verkeer onderdeel vormden van de doelfuncties. Uit de grote hoeveelheid beschikbare multicriteria GA's die zijn ontwikkeld, is in dit onderzoek een drietal algoritmes geselecteerd (nl. strength Pareto evolutionary algorithm 2 (SPEA2), het non-dominated sorting genetic algorithm II (NSGA-II) en strength Pareto evolutionary algorithm 2+ (SPEA2+)) op basis van hun prestaties op andere optimalisatieproblemen. Deze drie algoritmes zijn met elkaar vergeleken voor het MO NDP van dit onderzoek. De resultaten tonen aan dat het SPEA2 en met name SPEA2+ algoritme beter in staat zijn om een gevarieerde Pareto-optimale set te genereren in zowel de doelruimte als de oplossingsruimte dan het NSGAII algoritme. Echter het NSGAII en SPEA2+ algoritme presteren vergelijkbaar en beide beter dan SPEA2 in het genereren van de best presterende Pareto-optimale set. Alle heuristieken hebben echter nog altijd een groot aantal functie-evaluaties nodig. Voor elke functie-evaluatie is het noodzakelijk om het dynamisch gebruikersevenwicht te berekenen met het DTA model, hetgeen zeker in grotere toepassingen rekenintensief is. Om deze tijdrovende optimalisatieprocedures te versnellen, zijn in dit onderzoek drie algoritmes voorgesteld en getest, waarbinnen gebruik is gemaakt van response surface methoden (RSM) om een surrogaatmodel te schatten. Alle algoritmes gebruikten hierbij het SPEA2+ algoritme als basis. Vergelijking van de algoritmes, gegeven een vaste beschikbare rekentijd, laat zien dat het gebruik van RSM niet leidt tot het niet vinden van oplossingen in relevante onderdelen van de Pareto-optimale set. De gemiddelde prestatie van de algoritmes is vergelijkbaar en de ontwikkeling van de prestatiematen over de generaties laat zien dat het gebruik van RSM leidt tot een sterke versnelling van de zoektocht bij de start. Echter, de algoritmes die gebruik maken van RSM neigen naar snellere convergentie, mogelijk naar een lokaal optimum, en verliezen daardoor de voorsprong die ze in het begin hebben opgebouwd. Dit komt voornamelijk, omdat deze algoritmes afhankelijk zijn van de kwaliteit van het geschatte surrogaatmodel. Omdat rekentijden van belang zijn in het oplossen van MO NDP, zijn de

algoritmes die gebruik maken van RSM geschikt, met name voor grotere rekenintensieve netwerken.

Beslissingsondersteuning
Om een keuze te kunnen maken voor een oplossing is een compensatieprincipe nodig waarover een beleidsbeslissing noodzakelijk is. De Pareto-optimale set bevat waardevolle informatie om dit proces te ondersteunen, omdat hierdoor beleidsmakers kunnen leren over het probleem en mogelijke oplossingen, voordat een strategie gekozen wordt. Daarnaast heeft een multicriteria-optimalisatie het voordeel dat een keuze wordt gemaakt uit alle mogelijke strategieën in plaats van een keuze op basis van een beperkt aantal vooraf gedefinieerde strategieën. Dit onderzoek stelt een interactief beslissingsondersteunend systeem voor. Onderdeel hiervan zijn reductiemethoden en multicriteria-analyse (MCA). De reductiemethoden verkleinen de Pareto-optimale set met behoud van de belangrijkste karakteristieken van deze set. Het reduceren van de set kan geschikt zijn om de mogelijke moeilijkheden in het analyseren en begrijpen van de potentiële grote set te vereenvoudigen voor beslismakers. Drie methoden zijn vergeleken in dit onderzoek, namelijk convex hull, clustering en practically insignificance trade-off (PIT) filter. Clusteren kan worden gebruikt voor het analyseren van de belangrijkste keuzes, maar niet om een subset van oplossingen te selecteren aangezien het niet triviaal is om één representatieve oplossing voor een cluster te kiezen. De convex hull methode kan resulteren in een significante reductie van de Pareto-optimale set en is in overeenstemming met MCA-methoden waarin de doelstellingen lineair worden gewogen. Deze methode kan echter ook leiden tot het negeren van interessante delen van de doelruimte. Het PIT-filter is het meest geschikt voor het kiezen van een subset, aangezien deze methode is gerelateerd aan de veranderingen in trade-offs tussen oplossingen, waardoor de meest interessante oplossingen voor het beslisproces overblijven.

MCA methoden zijn methoden waarbij de best scorende oplossing wordt bepaald op basis van een bepaald compensatieprincipe. Kosten-batenanalyse (KBA) waarbij de effecten worden gemonetariseerd is een vaak toegepaste methode binnen verkeer en vervoer. De toepassing van KBA laat in dit onderzoek zien dat de reistijdverschillen en daardoor efficiëntie, verreweg het meest dominante doel is. Indien de beleidsmakers beslissen dat de economische afweging de methode dient te zijn om de doelen af te wegen, dan betekent dit dat het optimaliseren van de reistijden ook resulteert in de beste oplossing voor de externe effecten. De monetaire waarden zijn echter aan debat onderhevig en indien beleidsmakers de externe effecten meer serieus willen meenemen dan dienen andere MCA-methoden overwogen moeten worden. In dit onderzoek zijn de elementaire gewogen som (WSM) en gewogen product (WPM) alsook analytical hierarchy process (AHP) en de elimination et choix traduisant la realité III (ELECTRE III) methode toegepast. Het grootste verschil tussen WSM, WPM en AHP is de wijze waarop de doelen worden genormaliseerd, wat uiteraard ook de uiteindelijke uitkomsten en gevoeligheid voor de weegfactoren beïnvloedt. De ELECTRE III methode is de enige van deze methoden die rekening houdt met onzekerheid en is daardoor mogelijk een beter geschikte methode om uiteindelijk de beste oplossing te kiezen. Deze methode is echter complex, terwijl WSM en AHP meer transparant zijn en daardoor beter geschikt om in een interactief beslissingsondersteunend systeem te gebruiken.

Toepassingen
Om inzicht te geven in hoe DVM-maatregelen kunnen worden ingezet om de externe effecten van verkeer op een netwerkniveau te optimaliseren zijn de uitkomsten van een case met een synthetisch netwerk en een case met een realistisch netwerk van de stad Almelo gebruikt. In beide gevallen is te zien dat efficiëntie, luchtkwaliteit en klimaat in belangrijke mate

samengaan, maar tegenstrijdig zijn met geluid en verkeersveiligheid. Er bestaat echter niet één enkele oplossing die optimaal is voor meerdere doelstellingen, wat betekent dat er trade-offs bestaan tussen alle vijf de doelstellingen. Het optimale ontwerp voor efficiëntie richt zich op het vermijden van congestie, gebruikmakend van de volledige capaciteit van het netwerk. Het vermijden van congestie is ook van belang voor de emissies van stoffen. Aangezien voor luchtkwaliteit de emissies in stedelijk gebied hoger worden gewogen, zoekt het optimale ontwerp voor luchtkwaliteit een goede balans tussen het vermijden van congestie enerzijds en het gebruik van het onderliggende wegennet door stedelijk gebied anderzijds. In de synthetische case blijkt het optimale ontwerp voor de doelstellingen efficiëntie en klimaat vrijwel dezelfde te zijn. Dit is het gevolg van de aanname in het synthetische netwerk dat de capaciteit van de weg toeneemt bij een verlaging van de maximumsnelheid (homogeniserend effect) en het verlagen van de maximumsnelheid ook de emissies vermindert. In de realistische case van de stad Almelo is deze aanname niet gemaakt, zijn bovendien meer wegtypen meegenomen en bestaan er meer routekeuzemogelijkheden. Voor deze testcase verschilde daardoor het optimale ontwerp voor klimaat meer met die voor efficiëntie. De optimale ontwerpen voor de stad Almelo laten zien dat het vermijden van congestie ook goed is voor klimaat en luchtkwaliteit. Echter, het optimale ontwerp voor luchtkwaliteit en het optimale ontwerp voor klimaat doseert verkeer op specifieke locaties om omrijden en stroomafwaartse congestie te vermijden en het gebruik van de buitenring van de stad te vergroten, terwijl het optimale ontwerp voor efficiëntie de vertragingen meer verdeelt over het netwerk. Voor verkeersveiligheid probeert het optimale ontwerp het gebruik van de meest veilige routes via de snelweg zo groot mogelijk te maken en stedelijke routes te vermijden. Het optimale ontwerp voor geluid richt zich bij het gebruik van het RMV model op het zoveel mogelijk verlagen van de gereden snelheid en het vermijden van het gebruik van stedelijke routes. Wanneer de toename van het motorgeluid in congestiesituaties wordt meegenomen door toepassing van het AR-INTERIM-CM model, dan richt het optimale ontwerp zich nog steeds op het verlagen van de snelheid, maar ook op het vermijden van congestie op het onderliggende wegennet. In het laatste geval is geluid daardoor minder tegenstrijdig met efficiëntie. De nadere analyse van de Pareto-optimale set op basis van clusteranalyse, tevens voor delen van het netwerk, laat zien dat de verschillen tussen de clusters over het algemeen coherent zijn. Er bestaat dan ook een sterke correlatie tussen de afstanden in de doelruimte versus de afstanden in de oplossingsruimte van oplossingen. Echter, de verschillen binnen een cluster kunnen nog altijd significant zijn, terwijl deze vergelijkbaar presteren voor het gehele netwerk in de doelruimte. Het is daardoor mogelijk om in het beslisproces additionele criteria mee te nemen zoals billijkheid of complexiteit teneinde de beste oplossing te kiezen.

De cases in dit onderzoek laten zien dat er niet één enkele oplossing bestaat die alle doelstellingen tegelijkertijd optimaliseert. Het is echter mogelijk om, gegeven de relaties tussen de doelen, een generieke strategie te formuleren die in het algemeen geschikt is in de praktijk om de externe effecten van verkeer te verminderen. Omdat snelwegen over het algemeen buiten stedelijk gebied liggen en deze relatief veilig zijn, zou een generieke strategie kunnen zijn om het verkeer op de 'hogere orde'-wegen zoveel mogelijk te faciliteren, mogelijk in combinatie met een verlaging van de snelheidslimiet, verkeer te doseren en te bufferen op specifieke locaties (veelal bij de grenzen van het stedelijke gebied) en het verkeer in de stad zelf weer zoveel mogelijk te faciliteren en congestie daar te vermijden. Het doseren dient dan zodanig te worden toegepast om congestie te voorkomen in stedelijk gebied en de routekeuze dusdanig te beïnvloeden dat met name de 'hogere orde' wegen worden gebruikt. Waar het verkeer exact moet worden gedoseerd en in welke mate, is afhankelijk van de beschikbare routes, ruimtelijke ordening en de verkeersvraag in de specifieke situatie en kan daardoor complex zijn om in de praktijk te bepalen.

Implicaties en aanbevelingen voor nader onderzoek

De resultaten kunnen worden vertaald voor implicaties voor verschillende aspecten van verkeer en vervoer. Zo wordt het huidige proces van het formuleren van DVM-strategieën, zoals binnen het 'gebiedsgericht benutten'-proces, minder 'expert judgement' gebaseerd, omdat nu de doelstellingen daadwerkelijk worden geoptimaliseerd. Daarnaast zal de vertaling van strategieën richting maatregelen, procedures en algoritmen op tactisch niveau een grotere uitdaging worden, omdat de complexiteit om bijvoorbeeld 'triggers' te bepalen, toeneemt. Ook zullen er beleidsbeslissingen noodzakelijk zijn voor het te gebruiken compensatieprincipe. Daarnaast laten de cases zien dat het meenemen van de routekeuze-effecten belangrijk is. Het focussen op het verminderen van de externe effecten op lokaal niveau, kan leiden tot een verslechtering op netwerkniveau. Een andere implicatie is dat als DVM-strategieën worden ingezet om externe effecten te reduceren, waarbij het doseren van verkeer een mogelijke maatregel is, de in de huidige praktijk gebruikelijke toepassing van statische toedelingsmodellen als input voor het ex ante bepalen van de externe effecten minder geschikt is. Tenslotte kan het gebruik van DVM strategieën van invloed zijn op de ruimtelijke inrichting en infrastructuurplanning om de strategieën effectief te ondersteunen.

De volgende aanbevelingen kunnen worden gedaan voor nader onderzoek. Voor het modelraamwerk is onderzoek nodig naar het verbeteren van methoden om verkeersveiligheid te evalueren, rekening houdend met verkeersdynamiek. Ook is er nader onderzoek noodzakelijk naar de koppeling van verkeersmodellen met externe effectmodellen en de validatie daarvan. Er komt steeds meer kennis beschikbaar over de ongewenste effecten van verkeer als ook veranderingen in deze effecten door alternatief aangedreven auto's. Dit heeft consequenties voor het modelraamwerk. Daarnaast zijn er verschillende uitbreidingen van het raamwerk mogelijk met betrekking tot het verplaatsingsgedrag, robuustheid en vergroting van detail in de modellering van de DVM-maatregelen. Voor de oplossingsmethode blijven de rekentijden een aandachtspunt en nader onderzoek is gewenst naar het verkleinen daarvan. Met betrekking tot de beslissingsondersteuning is het noodzakelijk te onderzoeken welke informatie beleidsmakers precies willen hebben en hoe zij deze gebruiken. Daarnaast is onderzoek nodig naar geschikte afweegmethoden wanneer externe effecten worden meegenomen als doelstellingen. De toepassing van het raamwerk dient verder te worden uitgebreid, tevens in de praktijk, om de kennis te vergroten over het meenemen van de externe effecten. Dit is van belang om generieke strategieën te kunnen bepalen, maar ook om te begrijpen wat de gevolgen zijn voor de verschillende wegbeheerders, wat de gevolgen zijn als meer gedetailleerde doelstellingen en randvoorwaarden worden meegenomen of gedifferentieerde strategieën te ontwikkelen voor verschillende voertuigklasses. Tenslotte is nader onderzoek naar het meenemen van externe effecten als doelstellingen voor andere typen van beslisvariabelen of niet reguliere verkeerssituaties een interessante onderzoeksrichting.

Slotopmerkingen

Dit onderzoek heeft een geschikte aanpak opgeleverd om de externe effecten van verkeer mee te nemen als doelstellingen voor de inzet van dynamisch verkeersmanagement op netwerkniveau, rekening houdend met de verkeersdynamiek en routekeuze-effecten. Schaalbaarheid blijft daarbij een aandachtspunt, ondanks dat er in dit onderzoek methoden zijn gepresenteerd om deze schaalbaarheid te verbeteren. Gebaseerd op cases zijn inzichten verkregen over DVM-strategieën om de doelstellingen op netwerkniveau te optimaliseren. De resultaten van dit onderzoek hebben implicaties voor de inzet van DVM-maatregelen en beleid. Aanbevelingen voor nader onderzoek zijn gepresenteerd, waarbij de gedragsreacties en het begrijpen van het beslisproces belangrijke onderdelen zijn om uiteindelijk te komen tot succesvol duurzaam dynamisch verkeersmanagement.

Dankwoord

Precies in de week dat ik dit proefschrift heb opgeleverd om te versturen aan de leescommissie, is ons derde kindje geboren. Een groter geluk om een gezond kind te mogen krijgen, bestaat er eigenlijk niet. Je zou dus kunnen zeggen dat ik in één week twee bevallingen heb meegemaakt, hoewel de draagtijd van het vierde kindje wel wat langer was dan van de eerste drie. Iets meer dan vier jaar mocht ik me bezig houden met een onderwerp wat me nu nog steeds boeit en waar eigenlijk alles wat mij zo interesseert in dit vakgebied in samenkomt. Een dankwoord, dat ik vanwege mijn lezerspubliek in het Nederlands schrijf, is dan ook een mooi moment om eens terug te kijken op deze toch bijzondere tijd waarin velen een rol hebben gespeeld.

Na mijn afstuderen in 1999 sprak ik met Martin van Maarseveen en Eric van Berkum al over een mogelijk promotietraject. Ik had daar toen al wel oren naar, maar wilde eerst wat van de praktijk zien. Ik mocht aan de slag bij Goudappel Coffeng, waar ik tevens was afgestudeerd, en begon daar bij de groep verkeersmanagement. Hier mocht ik onderzoek doen met het nog steeds beste simulatiepakket dat er bestaat, INTEGRATION, en me bezig houden met onderzoeken gerelateerd aan gebiedsgericht benutten. Na een aantal jaren me bezig te hebben gehouden met verkeersmanagement, waarin ik veel heb geleerd van mensen als Martie, Marcel, Gert, Erik, Erik-Jan, Rolf en Job, kreeg ik de kans om me ook meer op evaluatieonderzoek te richten en wederom veel bij te leren. In eerste instantie met name veel met Geert en later ook met Paul en Robert. In deze periode groeide ook mijn interesse voor de externe effecten van verkeer. Dit kwam onder andere door projecten voor Agentschap NL zoals de evaluatie van Het Nieuwe Rijden en ook een fulltime detachering van een half jaar bij de SWOV in Leidschendam. Geert was inmiddels gaan werken voor Agentschap NL en tijdens een lunch ergens in 2004 kwam mijn ambitie om ooit nog eens te promoveren ter sprake. Geert gaf me de aanbeveling om, als ik die ambitie nog had, er nu toch wel werk van te gaan maken, want “als je eenmaal in een andere levensfase terecht komt dan wordt het een stuk minder eenvoudig”. Na wat gesprekken met Jaap en Gert en wederóm Martin en Eric, kwam de afspraak dat we een dergelijk traject zouden ingaan, indien ik externe financiering vond. Pogingen bij Casimir en Cornelis Lely mislukten helaas in 2005, waarna ik me er bij neerlegde dat het niet zou gaan lukken in de deeltijdconstructie zoals ik deze wenste.

In 2007 deed zich echter opnieuw een kans voor om een promotietraject te starten. Jaap stelde me voor om binnen TRANSUMO te starten met een dergelijk traject en zag dat duidelijk als een win-win-win situatie. Tot zijn verbazing zei ik in eerste instantie nee, omdat ik toen wist dat ik precies in de levensfase terecht zou gaan komen waar Geert op doelde. Bij de promotie van Wendy in 2007 begon het echter toch te kriebelen, zeker ook na de masterclass van Margareth Bell. Na een gesprek met Martin op diezelfde dag en het thuisfront had ik besloten om alsnog in te gaan op het aanbod om te gaan promoveren. De wil om dit onderzoek te mogen uitvoeren, bleek dus uiteindelijk toch groter en eind januari 2008 startte ik dan ook, wederom in Twente.

In 2008 startten we bij Goudappel ook met een nieuw team genaamd Transport innovatie en modellen (Tim), waarbij het logisch was dat ik daar onderdeel van zou gaan uitmaken. Hoewel het vertrek van Dirk bij de start van dit team een enorme aderlating was, kregen we er

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In Twente kwam ik op een vertrouwd nest. De vakgroep was weliswaar niet meer precies dezelfde als toen ik zelf in Twente studeerde, maar het voelde als vanouds. Een leuke groep mensen die bereid is om elkaar te helpen, zeg maar dat stapje te doen wat de spelers van het Nederlands elftal tijdens het EK 2012 niet wilden doen. Met name met Tom heb ik interessante gesprekken gevoerd over wetenschappelijk onderzoek op het gebied van verkeer en vervoer en mijn onderzoek. Ik hoop dat we in de toekomst nog vaker samen naar een congres mogen gaan. Thijs, mijn eerste kamergenoot, moet ik zeker bedanken voor het me enigszins de weg wijzen binnen de UT tijdens de start van het onderzoek. Verder wil ik natuurlijk Dorrette, Marieke, Sander, Wouter, Casper, Anthony, Jing, Jaap, Diana, Nina, Rudi, Sophie, Bart, Muzzafar, Mohamed, Bas en Malte bedanken voor de prettige tijd in Enschede. Daarnaast uiteraard de mensen waarmee ik binnen TRANSUMO heb samengewerkt waaronder Rob Hulleman en Frans van Waes. Ook TRAIL wil ik bedanken en dan in het bijzonder Conchita bij de laatste loodjes om dit verhaal gedrukt te krijgen.

Ieder hoofdstuk, alsook het proefschrift zelf, start met een uitspraak van Johan Cruijff. Dit is niet omdat ik idolaat ben van Johan (ik mag Johan zeggen), want ik was twee toen hij in 1978 zijn afscheidswedstrijd speelde. Daarna heeft hij, deels uit noodzaak, nog wel gevoetbald tot 1984, maar hij is niet echt van de generatie die ik me goed herinner. Johan staat voor mij symbool voor de sport welke voor mij de ideale uitlaatklep is. Ik kan genieten van het spelen van een partijtje en het dollen met de bal. Zou het toeval zijn dat FC Twente voor het eerst in de historie landskampioen werd, terwijl ik in Enschede bezig was met mijn onderzoek? In dat kader moet ik ook mijn voetbalteam bij SV Colmschate, zaterdag 1, bedanken voor de leuke trainingen en wedstrijden die we hebben gespeeld. Ik ben dan wel geen Deventenaar, was toch een soort Peter van All Stars, die jongen die er later pas bij kwam, maar ik voelde me meteen opgenomen in het vriendenteam. Ik hoop de komende jaren nog menig balletje op

woensdagavond met jullie te mogen trappen. Helaas heb ik wel tijdens de afgelopen vier jaar weer twee knieoperaties moeten ondergaan, waardoor ik me genoodzaakt voelde om de bondscoach te melden dat hij geen beroep meer op me kan doen. Bovendien gaat de leeftijd inmiddels ook meespelen en is het verstandig om jongere jongens een kans te geven. Om terug te komen op Johan; het voordeel is ook dat hij met geweldige uitspraken is gekomen die natuurlijk heel logisch zijn. Johan heeft er ook één gedaan over verkeer. "Mensen moeten harder gaan rijden, dan zijn ze sneller van de weg, dus zijn er minder files." Johan vergeet hier er even bij te zeggen dat hij dan wel aanneemt dat de volgafstanden ook bij hoge snelheden klein kunnen zijn. U merkt het al, Johan heeft overal verstand van.

Zijn uitspraak “Je gaat het pas zien als je het doorhebt” past in principe op ieder promotieonderzoek en zo ook op dat van mij. Tijdens een dergelijk traject ga je steeds beter je onderzoeksprobleem begrijpen en dus ook steeds beter zien waar het onderzoek naar toe zou moeten gaan. In dat kader, is het logisch om Eric te bedanken. Bij de start van het onderzoek had je het probleem beter door dan ik en zag je dus al zaken die ik nog moest ontdekken. Zonder jou was dit proefschrift er nooit gekomen, zeker ook door je steun en adviezen. Ook al lijk (of ben) ik een zeer eigenwijs en kritisch persoon, denk jij dat het onmogelijk voor me is om een spijkerbroek te kopen en mijn glas vaak half leeg is, ik heb zeer veel opgestoken van onze prettige voortgangsgesprekken.

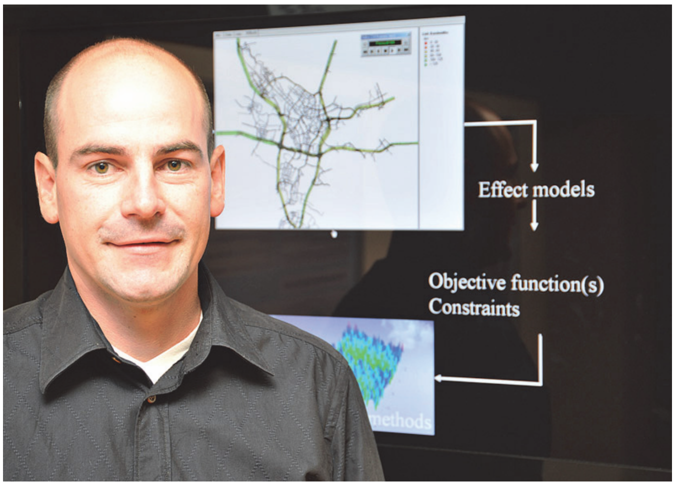
I also would like to thank the committee, putting effort in reading my dissertation and their willingness to travel all the way to Enschede to be part of my committee. The nice thing about my committee is that each one of you have influenced my work. I had the privilege to meet Prof. Rakha when I started my professional career at Goudappel when I was organizing the INTEGRATION user’s day. Back then, you were already working on quantifying emissions using microsimulation and developing VT-micro. Prof. Bell gave an inspiring master class on instrumented cities, which I attended and which was one of the reasons to start this PhD research. Prof. Bliemer was my colleague at Goudappel Coffeng, he learned me a lot and supported me as my team manager. I have met Prof. Tampère several times, mainly at conferences, where we had pleasant conversations, also about my research. Prof. Hoekstra reviewed my nine month proposal at the University Twente and gave me useful feed back. Dr. Geurs joined our research group after I started at the University Twente and our conversations at the TRB conference gave me some interesting ideas for my research.

Ook mijn vrienden en familie moet ik bedanken voor de getoonde interesse in de afgelopen jaren. In het bijzonder mijn ouders en schoonouders, die zo nu en dan bijsprongen als er iets geregeld moest worden voor de kinderen. Pa en Ma, jullie hebben mij de normen en waarden meegegeven waarmee ik in het leven sta en gestimuleerd in het benutten van talenten. Dit is ook belangrijk geweest om te blijven doorzetten en dit traject af te ronden. Jullie ondersteuning om in Enschede te gaan studeren, bleek voor mij een belangrijke en goede keuze voor mijn leven. Tijdens de afronding van mijn proefschrift moest ik regelmatig aan oma Wismans denken. Zij zei vroeger als we een rapport van de basisschool kwamen laten zien, “Gullie worden nog wel eens een keer professor”. Nu ga ik dat niet worden door dit proefschrift op te leveren, maar aan een zeer belangrijke voorwaarde daarvoor wordt hiermee wel voldaan.

Ik mag graag denken dat ik een afmaker ben. Ik ben dan wel geen spits, liever een nummer 10, maar als ik een bepaalde weg insla, dan wil ik het afmaken en ook op een zo goed mogelijke manier. Gelukkig heb en had ik daarbij de juiste mensen om me heen om daarbij te ondersteunen, waarvan ik reeds een aantal heb genoemd. Maar de belangrijkste heb ik nog niet genoemd en dat is mijn gezin, dat geleidelijk gegroeid is tijdens dit traject. We hebben samen al geweldige dingen meegemaakt, waarbij de vakanties echt hoogtepunten zijn. Else en Mats, elke keer als ik jullie op kwam halen "bij de kindjes" en jullie (gelukkig) vol enthousiasme me kwamen begroeten en de vrijdagen waarop ik me overdag met jullie mag vermaken, maken alles relatief en alles goed. Ik ben een gelukkig mens dat jullie en natuurlijk ook Minte onderdeel vormen van mijn leven. Eerlijkheidshalve moet ik bekennen dat ik ook K3 (voor Mats "Enne") moet bedanken, omdat het toch regelmatig voorkwam dat een DVD van hen uitkomst bood om nog wat te kunnen werken op de vrijdag aan mijn onderzoek. Minte, jou ken ik nog maar net, maar ik moet je nu al bedanken dat je een weekje later bent geboren dan de uitgerekende datum. Alsof je wist dat ik nog wat tijd nodig had om het verhaal af te ronden. Maar diegene die ik verreweg de meeste dank verschuldigd ben, is mijn beste vriendin sinds 16 jaar, waarmee ik inmiddels ook nog eens 5 jaar ben getrouwd. Jouw steun, advies, zorg voor mij (al dan niet als ik met krukken loop), zorg voor de kinderen (al dan niet als ik 's avonds of in het weekend aan het werk was, of congressen bezocht) hebben dit alles mogelijk gemaakt. Cécile, je bent simpelweg het beste wat mij is overkomen. Maar goed, dat is natuurlijk ook heel logisch.

Luc
Deventer, Augustus 2012

About the author



Luc Wismans was born on July 6th 1976 in Haalderen, part of the municipality Bemmel, the Netherlands. After finishing his masters in Civil Engineering & Management at the University of Twente in 1999 on optimization of dynamic traffic management measures on network level, he moved to Deventer to become a consultant traffic management at Goudappel Coffeng. He still lives in Deventer with his wife and three children. Starting as a consultant traffic management, research was focused on the effects of the deployment of traffic management measures using dynamic traffic assignment models and being involved in the development and application of the sustainable traffic management method as well as the operational translation in practice. During his career his focus slightly changed into research and development carrying out evaluation studies and development of innovations, which also resulted in a special interest in externalities of traffic. After eight years being active in the field of traffic and transport the opportunity presented itself to carry out a PhD research at the University of Twente on the optimization of externalities using DTM measures. A challenge to combine all interests and knowledge obtained, in one project, which he accepted in 2008. The same year a new research and development team was formed at Goudappel Coffeng called Transport innovation & modelling (Tim), which he joined from the beginning. This team takes initiatives and is a partner in creating innovative solutions in traffic and transport, seeking cooperation with others and model innovation is its main product. In 2012 Luc became team manager of Tim, which position he currently holds at Goudappel Coffeng.

Author's Publications

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"Het meenemen van externe effecten als geluid, emissies en verkeersveiligheid bij netwerkoptimalisatie van dynamisch verkeersmanagementmaatregelen, betekent een stap richting duurzaamheid.
In dit onderzoek is een raamwerk ontwikkeld waarbinnen de verschillende doelstellingen tegelijkertijd geoptimaliseerd worden, rekening houdend met routekeuzegedrag en verkeersdynamiek. Hierdoor ontstaat inzicht voor beleidsmakers en verkeerskundigen in hoe de doelen zich onderling verhouden en wat effectieve strategieën zijn voor verkeersmanagement."

- *Luc Wismans, onderzoeker Goudappel Coffeng*

"Leefbaarheid, bereikbaarheid, economische vitaliteit: mobiliteitsbeleid gaat in de kern over het goed afwegen van belangen en doelen. Het onderzoek van Luc levert een belangrijke bijdrage aan ons instrumentarium om juist bij die integrale benadering, met objectieve inzichten en reële vergelijkingen, tot optimale besluitvorming te komen."

- *Jaap Benschop, directeur Goudappel Groep*

Dit onderzoek is uitgevoerd in het kader van het Tim (*Transport Innovation & Modelling*) programma van Goudappel Coffeng in samenwerking met de Universiteit Twente en Transumo.

Samen met andere partijen, waaronder Omnitrans International en diverse universiteiten in binnen- en buitenland, werkt Tim aan het creëren van innovatieve oplossingen in verkeer en vervoer met modelinnovaties als kernproduct.

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