INTER-URBAN SHORT-TERM TRAFFIC CONGESTION PREDICTION

Giovanni Huisken

Dissertation committee:

prof. dr. F. Eising	University of Twente, chairman/secretary
prof. dr. ir. M.F.A.M. van Maarseveen	University of Twente, promotor
prof. dr. ir. E.C. van Berkum	University of Twente
prof. dr. ir. B. van Arem	University of Twente
prof. dr. A. Bagchi	University of Twente
prof. dr. ir. A. de Boer	University of Twente
prof. dr. H.J. Scholten	Free University, Amsterdam
dr. T. Brijs	University of Hasselt, Belgium

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TRAIL Research School
P.O. Box 5017
2600 GA Delft, The Netherlands
Telephone: +31 15 2786046
Telefax: +31 15 2784333
E-mail: info@rsTRAIL.nl

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prof. dr. ir. M.F.A.M. van Maarseveen

Voor Lidy en Alex

Preface

Traffic and transport are popular subjects for debate. Imagine, you are sitting at a bar or even better, you are at a birthday party. A certain person is asked what he does for his living. Then this person answers that he is involved in research on traffic congestion. Result: debate.

Very often, when I tried to explain the research subject I was working on, the conversation quickly transformed to a debate, especially when measures such as road pricing or toll collection were mentioned. Almost everybody has an opinion on these measures, one that I often heard being that these measures do not qualify as traffic management measures at all, but merely qualify as additional tax measures proposed by a money-hungry government. Always fun, talking about your work!

When I started my Ph.D. research, quite a few years ago, I had no clue on what traffic management was all about. I just left the University of Groningen, where I had concluded my Master's on pattern recognition of heart scan studies. Some months earlier, I had a conversation with a professor on traffic management (obviously, during a party!). I had experience with artificial neural networks, he had a student that did a research subject that involved traffic management and artificial neural networks and saw an opportunity for a Ph.D. research position on that subject. "Give me a call when you graduate", he said, and so I did. Now that I am not so clueless on traffic management any more and am standing at the eve of the long awaited closure of this part of my life, it is time for reflection and to thank some people.

First and foremost I am indebted to my supervisor prof. dr. Martin van Maarseveen, who gave me the chance to embark on this endeavour. Although I am certainly not the most easily manageable person, he was able to push my buttons in such a manner that this thesis did finally see the light of day. Martin, thank you for your almost infinite confidence in me, your guidance and the "nu speel ik even de advocaat van de duivel" conversations we had. Most supervisors most likely would not have had the endurance to see this through.

Prof. dr. Eric van Berkum is gratefully acknowledged for his profound knowledge and participation in conversations related to this Ph.D. research as well as conversations of more general nature. He is partly responsible for steering this research in a direction that I did not anticipate. Although additional efforts were necessary, it probably did improve the quality of the research considerably. Eric, additional thanks are in order for your participation in my dissertation committee.

Mascha, you were the student that chose the research subject on traffic management and artificial neural networks. Had it not been for you, I probably would not have been considered for this Ph.D. research position in the first place. Thanks, also for being my Ph.D. colleague at the Transport Research Centre. Marc, you were my first room-mate, albeit for a very short time. Thank you for showing me around, for the whiskey drinking evenings in South Africa and our joint three-day tour in South Korea. Mark, you also participated in these events. Furthermore, you have kept me company when we were working during the day, evening and weekends. Although our musical taste does differ, I was very fortunate to have you as my room-mate. Thanks also for agreeing to be my paranimf.

I am much obliged to my fellow Ph.D. students and the staff of the Civil Engineering department for creating a pleasant working environment. Thank you: Frans, Mako, Bart, Wendy, Martijn, Astrid, Henriëtte, Astrid, Pieter, Attila, Michiel, Henny, Leo, Bas, Kasper, Roland, Andrew and Marieke. Special thanks go to Dorette and Maureen for managing all administrative affairs (and more) at the Transport Research Centre.

In 1999, I was invited by prof. dr. Stephen Ritchie and prof. dr. Will Recker to join the Institute of Transportation Research, University of California, Irvine, USA for the last quarter of that year. Although the research work ultimately was not included in this thesis, it did result in conference papers and a journal article. Dear Stephen and Will, thanks for inviting me and for the useful discussions we had. And as Will said, Southern California is a nice place to be in autumn. I really enjoyed it.

The remaining members of the dissertation committee have taken the effort to read this thesis and to provide me with useful comments. Their efforts are highly appreciated.

I also thank the Traffic Research Department of the Dutch Ministry of Transport, Public Works and Water Management for providing a data set that was used in this research and additional data sets that I have used in other related studies.

After I left the University of Twente, I started working at ARCADIS. Although the economically circumstances were not favourable, I have learnt quite a lot in one year time and I want to thank my former colleagues for the experience.

In 2004 I started working at MuConsult. I am very grateful to prof. dr. Henk Meurs for giving me the opportunity to work at such a high quality consulting firm. Obviously, I want to thank everybody at MuConsult, especially Henk, Jan and Rinus, for what have been two inspiring years.

Since half a year I work at Capgemini. This has truly proven to be a great working environment, mainly due to the innovative projects and the great atmosphere provided by my colleagues. For that I thank:

Martijn, Ruud, Remi, Piet, Hans, Bart, Rob v H, Jacco, Rob B, Niels, Jeroen and others of the Mobility Group. I can hardly wait to find out what the future holds for us.

Dr. Peter Tsang and dr. Jill Curtis have taken up the burden to correct my writing into readable English. Many thanks for your efforts.

Dr. Sibrand Schepel flew me to the cloverleaf junctions 'Beekbergen' and 'Hoevelaken', so I was able to shoot some aerial pictures. During the flight I got my first practical flying lesson. Thank you!

Friends are necessary to relax, keep you grounded and to place things into perspective. Too many to mention individually, but I am sure that every one of you knows how I feel about you. Thanks a lot for your support; I will show my face more often.

Family is necessary to show you from time to time what is really important. Jurgen and Linda, your support is highly appreciated. Gerrit and Lidy, thanks for helping out whenever we asked you to. Felix, thanks for the discussions we occasionally have and for acting as my paranimf. Maurits, thanks for many pleasurable pool evenings so I could relax a bit and take my mind of research matters. It has been a while and we have to reinstate these evenings. Frans and Lenny, as my parents you have always supported me in my decisions and had a big influence on what I am today. Many thanks!

The year 2003 was a bad year. Not only did I lose my mother in law, also one of my dearest friends passed away unexpectedly. This thesis is dedicated to their memory.

Finally, I would like to express my deepest love to my wife Renate. Without your love and endless sacrifices this thesis would never have been finished. I cannot thank you enough for encouraging me and believing that I could manage to end this research, even when my own belief was gone from time to time. Teun and Sara, although I have neglected the both of you too much to write this book, I love you dearly. Hopefully, in a few years you will be able to understand the things I was working on when I should have spent more time with you. Until then, I will give my best to make it up to you.

This endeavour has proven to be a long and bumpy ride, sometimes tough, always interesting. It ends here.

Oldenzaal, November 2006,

Gio

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Contents

CHAPTER 1

Introduction

"Begin at the beginning, and go on till you come to the end: then stop."

King of Hearts in: 'Alice in Wonderland'

1.1 Background

Since the invention of the wheel, mobility of mankind has increased. Now that we are at the beginning of the twenty-first century, the transport systems of many developed countries suffer from serious problems. Although mobility growth goes hand in hand with increasing prosperity (figure 1.1 shows an indexed graph of mobility related to the Gross Domestic Product of European countries during the last decade of the 20th century), it generates also negative side effects, especially due to car mobility, these demonstrate themselves nowadays in particular during morning and evening peak hours: accidents and congestion leading to traffic victims, economic costs and environmental damage (Ministry of Transport, Public Works and Water Management, 1990, 1996, 1998, 2001). Additionally, congestion increases the uncertainty of journey times leading to stress and unsafe traffic situations. The afore-mentioned side effects are partly caused by the inability of expanding infrastructure to keep up with increasing car traffic movements. How can we reduce these problems?

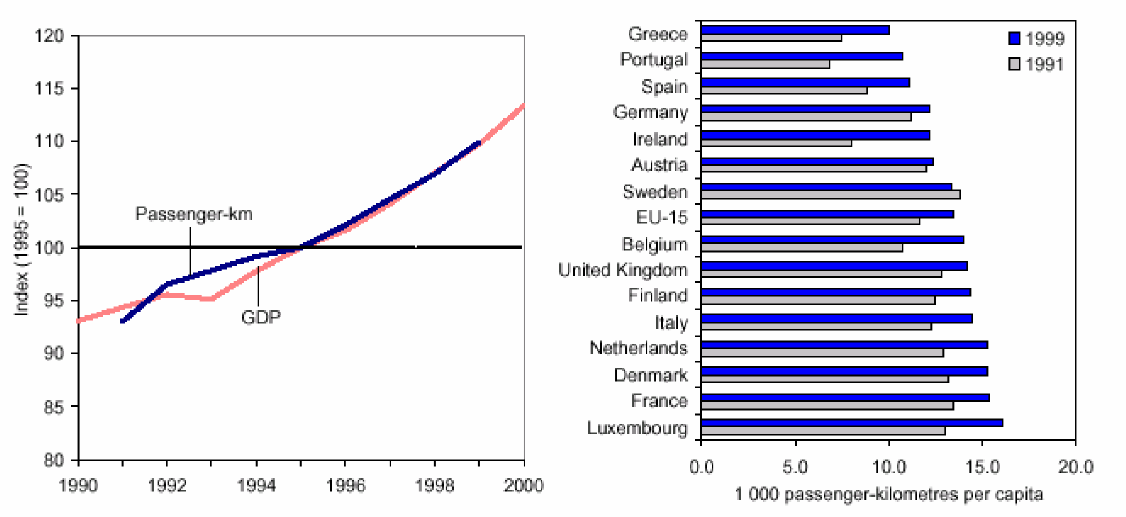

Figure 1.1: *Passenger transport demand and GDP (EU),*
Source*: Eurostat, 2002*

Mobility within transport systems can be regarded as a matter of travel demand and infrastructure supply. The problems are predominantly caused by cars. They occur whenever car travel demand exceeds infrastructure supply resulting in congestion. We can try to lessen these problems by either cutting back on car travel demand or by increasing infrastructure supply. On one hand, we can cut back on car travel demand by persuading car travellers to change over to another mode of transport such as public transport or by inflicting penalties for the usage of infrastructure. Numerous measures have been proposed as solutions (see e.g. Ministry of Transport, Public Works and Water Management, 1990, 1996, 1997a-c, 1998, 2001; European Commission,

2001) and some of them are also mentioned below. On the other hand we can increase the infrastructure supply by simply adding extra infrastructure, especially at bottlenecks. Are there any other solutions at hand? Yes, there are: They involve measures that increase the efficiency of infrastructure in time and/or space.

So, the measures can be divided into the following solution categories:
- Discourage the use of cars;
- Encourage the switch from car use to alternative modes of transport;
- Increase the amount of infrastructure;
- Increase the efficiency of the infrastructure in time (temporally);
- Increase the efficiency of the infrastructure in space (spatially).

The first four categories will be discussed briefly while the fifth is the subject of this thesis and therefore will be discussed in more detail. The first two categories are based on decreasing mobility or keeping mobility at the same level by switching to another form of transport, whereas the latter three are based on increasing the (efficiency of the) infrastructure and thus obtaining a higher mobility.

1.1.1 Discourage the use of cars

There are several ways to discourage car use and usually the measures can be carried out by infliction of time or money penalties. Examples of such measures are the increase of fuel tax (Rietveld *et al.*, 2001), the increase of infrastructure tax (Enis and Morash, 1993), and the increase of the tax that has to be paid when purchasing a new car (Hayashi *et al.*, 2001). Other options are the installation of pay-lanes and tax-lanes (Verhoef, 2002), the introduction of road pricing (Ferrari, 1995; Yang and Bell, 1997; Pieper, 2001), and the equalisation of the attractiveness of neighbouring regions, e.g. by inflicting another parking pricing policy to keep certain areas traffic-low (Hensher and King, 2001). However, these measures are based on an attitude change and therefore will take a long time (e.g. a change of law) while community support has to be gained before results can be observed. Furthermore, they may have a negative impact on the economy because of decreasing mobility. Therefore, these measures will not be the subject of the present research.

1.1.2 Encourage the switch from cars to other modes of transport

Although mode switching, especially from cars to an alternative mode of transport, is a real challenge to policy makers (O'Fallon, 2002), there are some options to switching from car to bicycle or public transport.

First of all one can use one (or more) of the methods mentioned in section 1.1.1 and/or improve collective transport; i.e. decrease the ticket price (Huang, 2002), increase the amount of buses or trains per hour between certain origins and destinations (Cascetta and Papola, 2003), improve the runs in connection (Kottenhoff and Lindh, 1996), and make collective transport more comfortable (de Palma and Rochat, 2000). Other methods involve better and safer bicycle and pedestrian lanes and conditions. However, these measures are usually very expensive, especially in non-urban regions, and are also based on an attitude change. Therefore, these measures will not be the subject of the present research.

1.1.3 Increase the amount of infrastructure

Until the 1980's the predominant response was simply to increase the amount of infrastructure at the sites of congestion. Since then this option has suffered from decreasing popularity due to its huge costs (in terms of money as well as space) in Western Europe. However, it will not be a topic of discussion in the remainder of this research because the results in the long term seem rather unattractive; examples of this option are metropolitan areas such as Los Angeles, Tokyo, and Singapore. In addition to costs, another phenomenon emerges: induced traffic (Goodwin, 1996; Noland, 2001). The theory of induced travel is based upon the simple economic theory of supply and demand. When any good, say travel, is reduced in cost, the quantity demanded of that good increases. A change in a transport condition, such as a capacity increase, can reduce the generalized costs of travel. As a result the demand for travel increases. The optimum point may have been reached in some places, and for other places the optimum was reached probably a long time ago. Studies in this field of research are currently ongoing (Zuidgeest *et al.*, 2002; Zuidgeest, 2005).

1.1.4 Increase the temporal efficiency of the infrastructure

When we look at the utilisation of the motorway infrastructure system, we can see that its use is very inefficient: the traffic intensities are low during the majority (non-peak hours) of the day. For instance: in The Netherlands we have the following figures for the year 2000 (Transport Research Centre, 2003):

- Amount of vehicle kilometres on motorways, travelled during working days: 36 billion;
- Amount of motorway lane kilometres: 11,081.

Then we have the obvious figures:

- Working days during the year 2000: 250;
- Hours per day: 24;
- Capacity of a lane: 2,100 vehicles per hour.

These numbers result in an I/C ratio (intensity over capacity ratio; a ratio that quantifies usability) of 26 % per twenty-four hours on working days and show that there is (in theory) room for spatial efficiency improvement. However, because the bulk of congestion traffic on motorways during peak hours is formed by business and through traffic, the increase of efficiency of the infrastructure in time is rather difficult to achieve because the majority of companies are still confined to '9 to 5' working-hours for the majority of their employees. These uniform working hours are still the most prominent reason for the morning and evening peak hours.

One way to solve this would be wide spread flexible working-hours (and this solution can be improved by making use of road pricing) but this is for most companies not very economical because the majority of business transactions are done with companies in the same time zone. It may also disrupt social functioning of society. Other suggested measures to partly solve this is to let people work at home, the so-called tele-working (Giuliano and Gillespie, 1997; Limburg, 2002), by cutting back business travel by making use of video-conferencing, tele-medicine, and distance education (Golob and Regan, 2001), or through the influence of e-commerce and tele-shopping (Golob, 2000; Lyons, 2002). In how far these measures will actually relieve the transport systems is still a matter of debate: future research will have to provide the answers to that question. In fact, tele-working for example is not incorporated into society as was predicted a decade ago (probably due to the perceived difficulty of managing personnel at a distance and isolation) and thus the effects are not as significant as was predicted. Also, the way in which these IT-applications generate other traffic streams (e.g. transport of goods due to tele-shopping) is object of ongoing research. Therefore, we leave the research of this interesting but somewhat disappointing solution to others and focus on the next solution.

1.1.5 Increase the spatial efficiency of the infrastructure

When we take a look at quantitative analysis of the motorway network of the Netherlands (Transport Research Centre, 2003) and take into account the numbers given in the previous section, they indicate that next to a temporal also a spatial efficiency increase can be made. Whenever we want to increase the spatial efficiency of the infrastructure we have to assess traffic on a network scale and therefore manage traffic on that scale. Management decisions depend on the amount of traffic that uses the transport system and is therefore dynamic in nature. We can categorise these Dynamic Traffic Management (DTM) decisions as long-term or short-term decisions. Long-term decisions deal with planning and are about location and impact of measures. Usually these measures are simulated within computer models to learn about the results they generate and sometimes are done in combination with traditional traffic engineering such as the construction of new roads. Typical examples are High Occupancy Vehicle (HOV) lanes, bus lanes, Dynamic Road Markings and peak lanes. Short-term decisions are taken as a result of the current or near-future state of the transport system and not only known as DTM measures but also as Traffic Control. Often these measures are made by computers without human interference. Typical examples are vehicle actuated traffic light control and local ramp metering. DTM provides tools to alleviate congestion by increasing the spatial efficiency of the infrastructure and will be looked at in more detail in the remainder of this chapter.

1.2 Dynamic Traffic Management

Dynamic Traffic Management uses technologies for real-time traffic monitoring, network wide traffic management of traffic flows, and traffic adaptive control to respond to changing traffic conditions. However, DTM is not only applied to the efficiency of the infrastructure, it is also used to improve traffic safety and travel conditions and to reduce energy use and the environmental impact of traffic. Further use can be found in increasing the efficiency of vehicle fleets and improving the attractiveness of public transport and thus overlaps with the field of Intelligent Transport Systems. All these promises have led to big ITS/DTM programs all over the world. We take a quick glimpse at how the global deployment of these programs took place.

1.2.1 DTM global deployment

It was not until the 1980's that attention was paid to the spatial increase of the efficiency of the infrastructure; before this the common policy was simply to build new roads or increase the number of lanes. In short: the solution generally consisted of adding additional asphalt at problem spots or laying out new roads. Due to difficulties in area planning in crowded countries (e.g. the Netherlands) or crowded cities (e.g. Tokyo, Los Angeles, Seoul) the increase of efficiency of infrastructure received attention as a possible remedy for these problems and this relatively new field of traffic management is now know as Dynamic Traffic Management.

World wide there are three large government programs that act as an umbrella for ITS/DTM transport research studies. The European Community (EC) launched the Dedicated Road Infrastructure for VEhicle safety in Europe (DRIVE) program in 1988 (Boesefeldt and Neuherz, 1993; Klijnhout, 1993), the USA started the Intelligent Vehicle/Highway Systems (IVHS) program in 1990 (Judycki and Euler, 1993; Klein *et al*, 1993), and the Vehicle Information and Communication System (VICS) program originated in Japan during the early 1970's (Upchurch, 1993). More details on the history of DTM are available in Appendix A.

1.2.2 DTM measures / Traffic control

When we take a closer look at DTM we can identify several common stages that are present during successful functioning of the process, ranging from data acquisition to information reception by the driver (see bow tie figure 1.2):

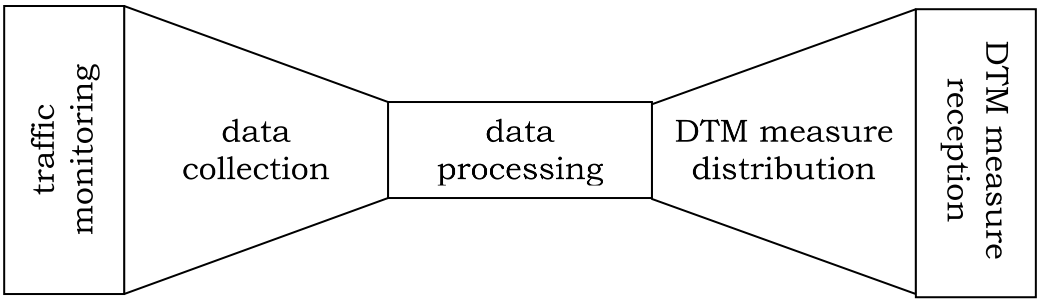

Figure 1.2: *From data acquisition to DTM measure reception*

- *The monitoring stage*: It is important to gain information on the current state of the traffic systems, the infrastructure network and the load on it. In order to receive this kind of information we need to monitor the transport systems. There are several techniques that are available for monitoring, such as (dual) induction loops, cameras, various kinds of sensors (microwave, infrared, acoustic, electromagnetic, etc.), and probe vehicles (more details can be found in Appendix B);

- *The collection stage*: Monitoring data are collected at the points where traffic management decisions are taken, i.e. (sub)-local for signalised intersections and central where traffic management decisions are taken that have a network-wide impact. Data are sent as electric signals through copper wire, as light signals through fibre optics, as Electro Magnetic signals through air, and/or by using a combination of these techniques in order to reach the central area of collection;

- *The processing stage*: When data is collected at a central point it has to be processed to interpret and estimate the current and possible future state of the transport system and to recognise if there are problems now or in the near future. The current or near-future state of the system will then act as a trigger whether or not to deploy certain DTM measures;

- *The distribution stage*: Once the decision has been taken to deploy DTM measures the prevalent DTM measures have to be disseminated to the appropriate vehicle drivers. The selected DTM measures are displayed on e.g. Variable Message Sign posts or, more directly, variable speed limits are given. Other means of distribution are by FM radio, Digital Audio Broadcasting, other (advanced) roadside-based systems (e.g. the Graphical Message Sign post), mobile phone, the Internet, or navigation systems (Huisken and Van Berkum, 2000);

- *The reception stage*: Finally, the vehicle driver has to become aware of the DTM measure and take appropriate action. This means that information regarding the DTM measure has to be perceived and correctly understood by the driver. Subsequently, an adjustment of behaviour has to take place (at least by a percentage of drivers); this in turn has to lead to the anticipated traffic flow alteration. Now, to display a certain DTM measure and to act on it are two entirely different aspects (Mannering, 1989; Khattak *et* al., 1991, 1993; Van Der Mede and Van Berkum, 1993; Emmerink *et al.*, 1996). One step further would be to choose DTM measures that already take the driver's responses into account, so-called anticipatory DTM measures (Taale and Van Zuylen, 2003a and 2003b).

The first and latter two stages are getting a lot of attention at the moment and are improved constantly. However, DTM measures depend on the total chain and are therefore as successful as the weakest link in the chain. Often this is the processing stage; this has to do with the moment of activation of DTM measures. To understand why the moment of activation of DTM measures can have a major impact on the throughput of the resulting traffic flow we will have to take a closer look at the traffic flow theory underlying the process in the next section and point out where gains can be made.

1.3 Traffic flow theory

Traffic flow theory is based on common sense and observation (or monitoring) of traffic phenomena. The subsequent description of traffic flow phenomena can be done at a microscopic (vehicular) level, at a macroscopic (traffic stream) level, and at an intermediate 'mesoscopic' (packets of vehicles) level. This is achieved by defining a number of mathematical variables that are assigned to a one-dimensional time-distance description of the motion generated by traffic vehicles, particularly on motorways. Traffic flow theory is the basis for building traffic models.

1.3.1 Microscopic level

In the microscopic description of a traffic stream each vehicle is considered separately. Let us examine vehicle *a* on a road; its position can be indicated by x_a. The vehicle upstream of *a* can be identified as *a-1*. Both vehicles travel along the road and therefore the position of x_{a-1} and x_a is time dependent, $x_{a-1}(t)$ and $x_a(t)$, respectively. A time-distance diagram, as shown in figure 1.3, where the trajectories represent the position of the vehicle through time and thus explain the variables. Lane changing involves an additional dimension and can also be described at the microscopic level.

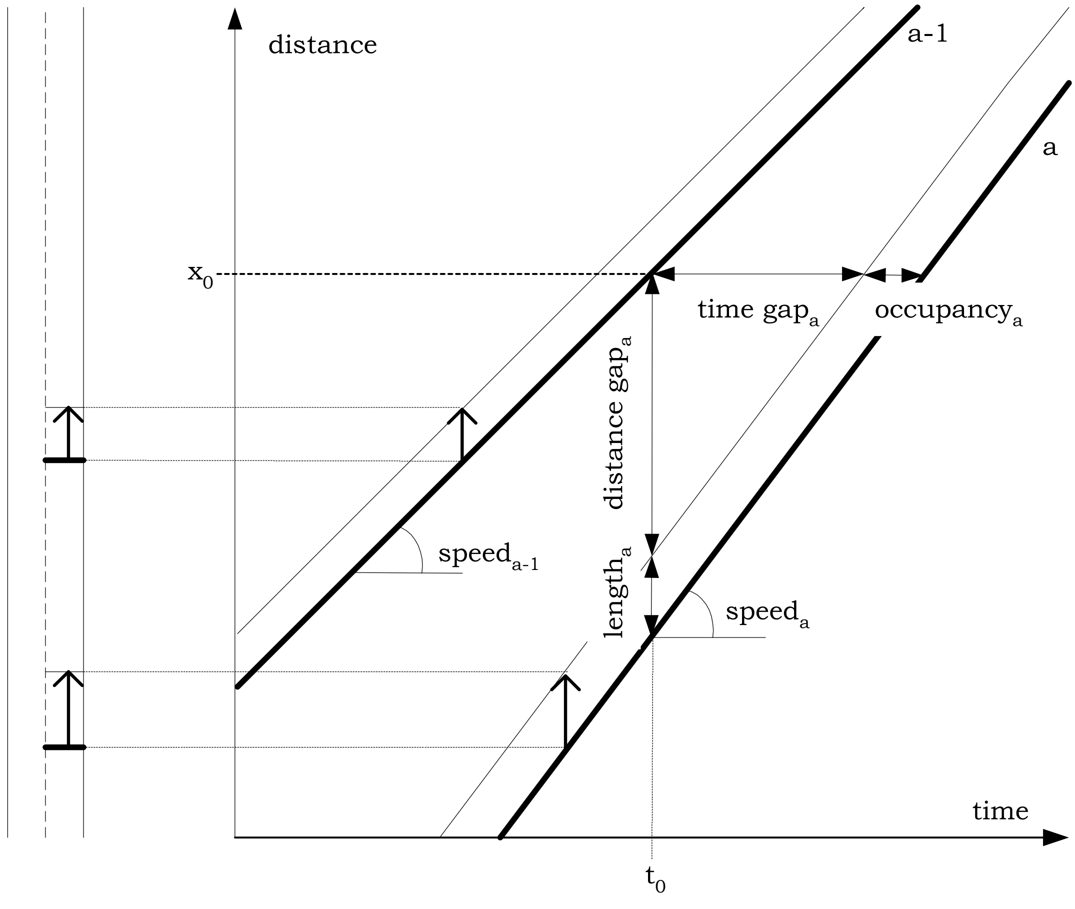

Figure 1.3: *Time – distance diagram of two vehicles (adapted; Logghe, 2003).*

The speeds of the vehicles are given by the derivatives of their trajectories, the accelerations by the second derivatives (equation 1.1).

$$acc_a(t) = \frac{\partial v_a(t)}{\partial t} = \frac{\partial^2 x_a(t)}{\partial t^2} \tag{1.1}$$

Consider a vehicle a where the rear bumper of the vehicle is used as point of reference. When looking at the horizontal axis of figure 1.1 (time) we can see that at time t = t_0 this vehicle has a certain fixed $length_a$ and a distance $gap_a(t_0)$ between its front bumper and the rear bumper of the next upstream vehicle x_{a-1}. Therefore, at time t = t_0, vehicle a occupies the total space (from the rear bumper of vehicle a to the rear bumper of vehicle $a-1$) of $space_a(t_0)$ = $length_a$ + $gap_a(t_0)$.

Similarly, the vertical axis of figure 1.1 (distance) can be considered. At distance x = x_0 the total headway (from the rear bumper of vehicle a to the rear bumper of vehicle $a-1$) is given by $headway_a$ = $occupancy_a$ + time gap_a.

1.3.3 Mesoscopic level

At the mesoscopic level, traffic streams are treated as packets of vehicles or user classes. It is postulated that the approach of distinguishing user classes and their specific driving characteristics will improve both the accuracy and the explanatory ability of traffic flow models significantly (Hoogendoorn and Bovy, 2000). In case of user-classes, traffic flow on a mesoscopic level can be described by using gas-kinetic equations on distinctive user classes of vehicles, describing the dynamics of the class-dependent spatial density, speed and variance of speed (Hoogendoorn and Bovy, 2001). The equilibrium relations of the gas-kinetic equations show competing processes of:

- Acceleration towards class-dependent desired speed;
- Deceleration due to class-specific interactions;
- Asymmetric interactions between mutual classes.

Starting point for the derivation of the macroscopic flow model is the user-class specific phase–space density, which can be considered as a generalisation of the traditional density.

1.3.2 Macroscopic level

At the macroscopic level, vehicles are treated at an aggregated scale and not as separate entities. As a result the discrete nature of traffic is switched over to a continuous description: traffic flows. The three main accompanying variables are defined as:

- Density k is a variable that is typically used in physics that has been adopted by traffic science. Density k indicates the number of vehicles for each kilometre of road. Measuring k across a road section with ΔX at a certain point in time is simply:

$$k = \frac{n}{\Delta X} \tag{1.2}$$

  Here, n represents the number of vehicles present at the road interval ΔX at that point in time. One could think of a helicopter snap-shot of the road to estimate k;

- Flow q can be compared to the flux of a stream. The flow, or intensity, reflects the number of vehicles passing a point during a certain time interval. Measuring q during a period ΔT at a certain location gives:

$$q = \frac{m}{\Delta T} \tag{1.3}$$

  Here, m represents the number of vehicles that passed a certain location during period ΔT at that point in time;

- Average speed u can be defined as the quotient of flow and density. Subsequently, average speed depends on location, the point in time and the measurement interval and can be written as:

$$u = \frac{q}{k} \quad or \quad q = k.u \tag{1.4}$$

  Since k is measured over a road section at one point in time and q is measured over a period of time at one particular location, equation (1.4) only holds if both limits of the time period and road section are taken infinitely small. When either of these circumstances does not apply, equation (1.4) has to be regarded as an estimate.

Based on the macroscopic definitions of flow q, density k and mean speed u, we have two independent macroscopic variables (bounded through their mutual dependency). Based on observations, Greenshields (1934) was the first to attempt to establish a relation between the remaining independent variables. Later, Lighthill and Whitham (1955) and Richards (1956) developed independently a theory relating all 3 variables called the continuum theory (or LWR theory). The relationship can be depicted in a diagram; the fundamental *k*-*q* diagram (figure 1.4).

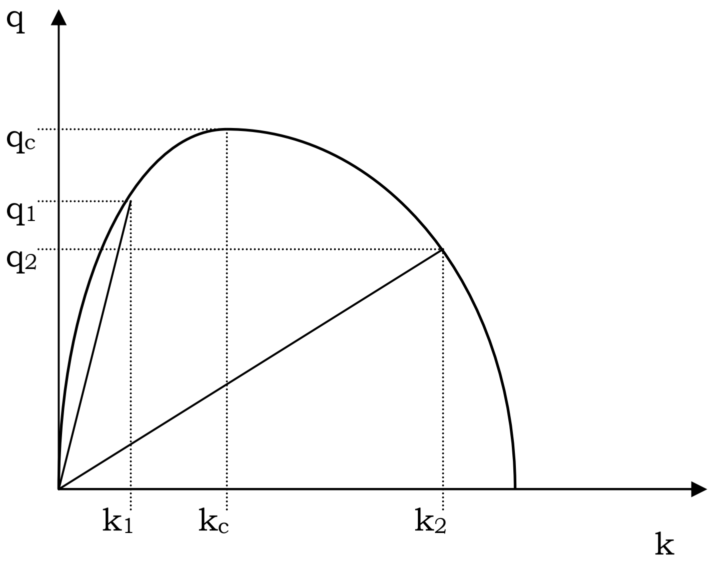

Figure 1.4: *The fundamental k-q diagram.*

The fundamental *k*-*q* diagram shows schematically how *q* and *k* are related to each other on a certain road section. Points lying on the diagram can be presented as (k, q) and from this we can estimate speed *u* by using equation (1.4). Maximum flow (intensity) is reached at point (k_c, q_c); this is the capacity of the road section. Whenever density *k* is lower than k_c we speak of free-flow traffic, e.g. at point (k_1, q_1). Subsequently, at point (k_2, q_2), where density *k* is higher than k_c we speak of congested traffic. When the traffic flow reaches capacity and the density increases the traffic flow finds itself in the congested regime where it usually takes a long period of time to regenerate and move back to the free-flow traffic regime. This phenomenon is known as hysteresis.

1.3.4 Hysteresis

Hysteresis has been studied by, among others, Treiterer and Myers (1974) and Maes (1979). In the former study aerial photographs were used to analyse traffic speed and concentration by tracking a vehicle stream as it went through a disturbed regime. In the latter study inductive loop data, aggregated into 1-minute time bins, were used to examine the relationships between occupancy, flow and speed under transient traffic conditions caused by incidents. Both studies concluded that the evidence suggests that hysteresis is generated through individual time gaps between vehicles due to widely varying acceleration and deceleration rates and is therefore of microscopic nature. The variation in acceleration and deceleration is, according to Cassady (1998), also responsible for data scatter in the congested branch area of fundamental graphs made out of real data. Although the studies reported different occupancy vs. speed graphs (see figures 1.5a and 1.5b), a possible explanation accounting for the differences is, according to Zhang (1999), due to the data aggregation level. The author comes to this conclusion by attempting to unify the observations into a mathematical theory.

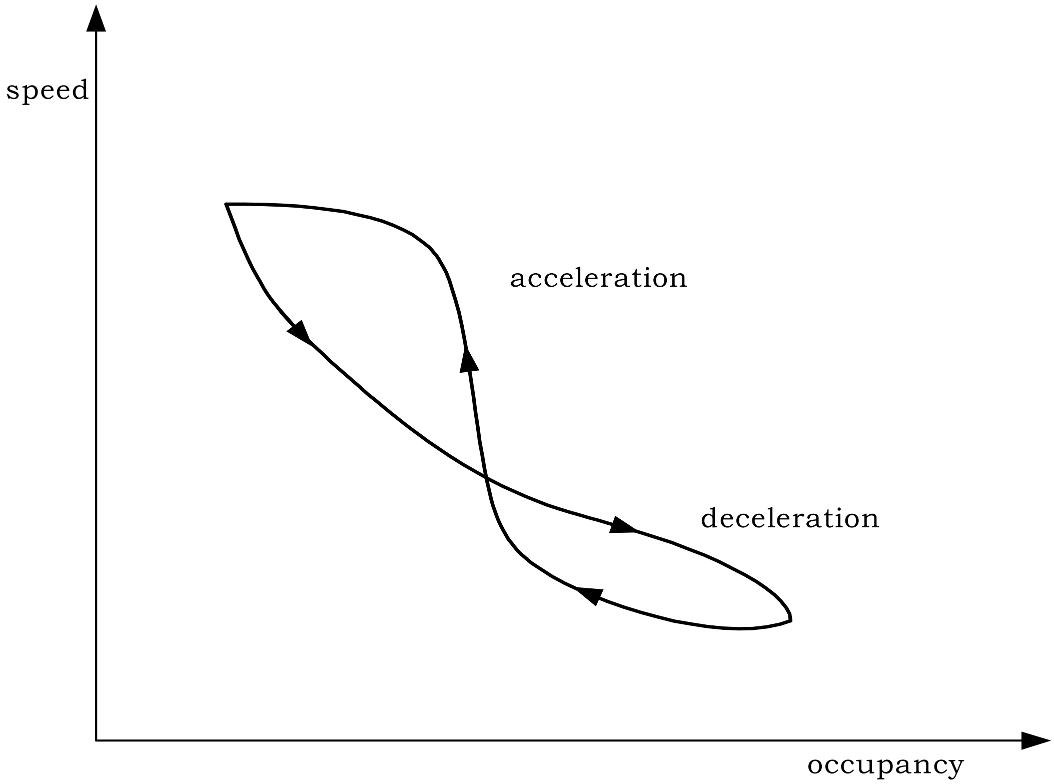

Figure 1.5a: *Trajectory for occupancy(x,t) vs. speed(x,t), adapted from Treiterer and Meyers.*

Hysteris can take many forms. It is exactly this feature that causes great difficulties for existing traffic flow theory based traffic models to predict congestion. The severity and length of congested periods are often poorly modelled.

The objective of activating anticipating DTM measures is to control the traffic flow in such a manner that the traffic stream stays away from the congested regime and thus alleviates congestion. Examples of measures are the deployment of ramp metering (Zhang and Ritchie, 1997; Alessandri *et al.*, 1998; Kotsialos *et al.*, 2002; Smaragdis *et al.*, 2004), route guidance (Papageorgiou, 1990; Hawas and Mahmassani, 1995; Kachroo and Özbay, 1998) and variable speed limits (Kotsialos and Papageorgiou, 2004). Hence, this calls for a prediction tool that can predict reliably whether or not congestion will set in if no measures are taken and so we arrive at the objective and justification of the present research.

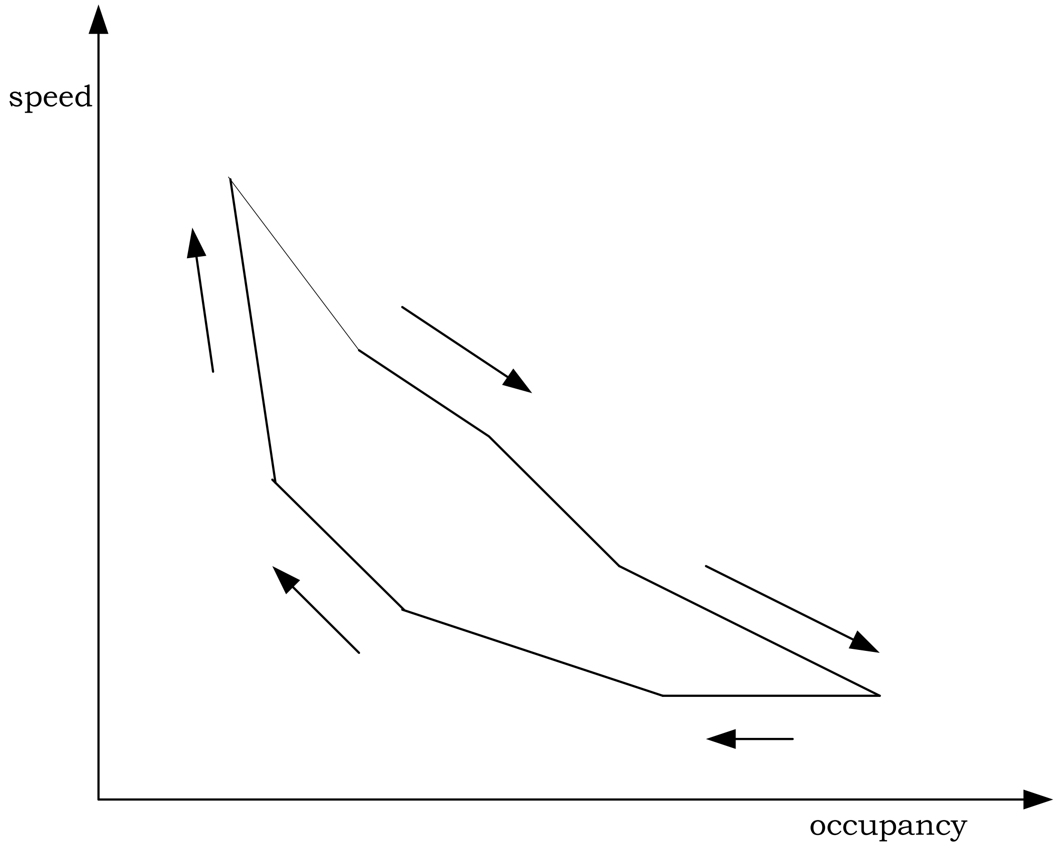

Figure 1.5b: *Trajectory for occupancy(x,t) vs. speed(x,t), adapted from Maes.*

1.4 Objective and justification of the present study

Here the reasons for the necessity and the goal of this research will be discussed. As was mentioned previously, congestion is responsible for various assessments on the community. One way to reduce congestion would be by means of DTM measures. Unfortunately, it is currently widespread policy to activate these measures *after* congestion has already occurred and the traffic flow has broken down resulting in time-consuming traffic flow regeneration. It is therefore important to have some knowledge about traffic conditions in advance so anticipating DTM measures could be taken to alleviate congestion and keep the traffic flow going. A tool that could accomplish such would ideally predict if congestion would occur within the short-term future with high reliability. So there is need for a robust short-term congestion prediction tool.

Before short-term traffic congestion prediction tools are to be implemented it would be wise to have some indications as to which particular tool (based on a specific method) to use under that particular circumstance. Hence, there is need for a comparative study of the performances of several methods that can be used to predict congestion within the short-term time horizon, i.e. 5 – 30 minutes look ahead period.

Therefore, the main research question that can be derived from the above is:

> *Which of the methods gives the best congestion predictions on motorways within the short-term horizon and under what circumstances are these predictions achieved?*

Before this question can be answered there is need for a more detailed extension by means of definitions of the terms used. To do so literature will be researched to find out what the current state-of-the-art is. What has already been done with regard to similar or closely related research issues; what methods have been used to come to results, what were the circumstances (which horizons were used, what kind of monitoring data was used, which aggregation level was used) at which they were achieved and how were these results measured? This information will then be used to select methods that seem successful and decide on the circumstances at which their performance will be measured and how the results will be evaluated.

1.5 Outline of the thesis

Chapter 2 provides an overview of the current state-of-the-art. It contains a literature review concerning research on short-term congestion prediction and related topics such as short-term prediction of traffic volume and travel time prediction. In this chapter which methods have been used to study these topics and how their performances were assessed is subject of research: the data sets that were used and, more specific the aggregation level, and the calibration and evaluation process of the models at hand. Consequently this will result in the ability to specify the research question and will then lead to a more detailed research approach.

Chapter 3 describes the fundamentals of the methods used in this research. Although the descriptions are not comprehensive, several references are given for more in-depth information on these methods.

Chapter 4 presents the acquisition sites. The cases being the cloverleaf infrastructure architecture 'Beekbergen' of motorway A1 with motorway A50; and the cloverleaf infrastructure architecture 'Hoevelaken' of motorway A1 with motorway A28.

Chapter 5 postulates transport related hypotheses. It is the main objective of this research to either confirm or reject these hypotheses and since the majority of the hypotheses are method- or infrastructure site-based they are given in chapter 5 rather than in the perhaps more intuitive introductory chapter.

Chapter 6 incorporates the necessary steps that were taken during the pre-processing of the gathered data. It describes how and why data was transformed from the original detector data into data that can be used during the calibration and evaluation processes.

Chapter 7 informs on model development. All methods are developed into congestion prediction models and their input / output parameters are discussed. Also additional information regarding model architectures is given.

Chapter 8 is about the results of the methods' performances and by analysing these results to either confirm or reject the hypotheses given in chapter 5, in other words: which method predicts congestion with the best results and under what circumstances did that take place.

Chapter 9 ends this thesis and discusses what general conclusions can be drawn from the entire research with respect to the postulated hypotheses. Furthermore, overall conclusions and their implications of this research are given. Finally, some directions for further research are identified.

CHAPTER 2

Literature review

"Reading is sometimes an ingenious device for avoiding thought."

Sir Arthur Helps

2.1 Introduction

The purpose of this chapter is to find out which research has been carried out with respect to congestion prediction and to establish the current state-of-the-art. Found omissions and general research results will give clues on how to set up the research approach considering issues like e.g. data acquisition, data aggregation level, the choice of modelling techniques, and the choice of measurements of effectiveness during the evaluation phase. In this chapter the focus will therefore be on research that can be categorised in the data processing stage (figure 2.1), and to be more specific: traffic status estimation and traffic prediction research.

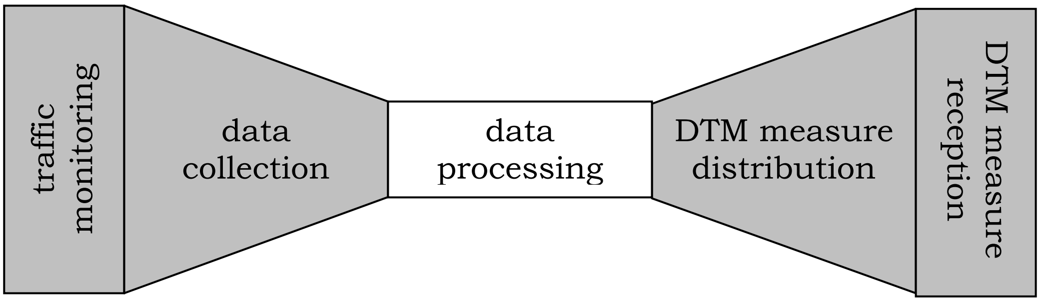

Figure 2.1: *The data processing stage in the DTM scheme*

First a review of the literature on several techniques that have been used to come to the estimation or prediction of the state of the traffic system will be carried out. The purpose is to identify the methods with good credentials for traffic prediction. Now, since the subject of this thesis is congestion prediction, research already performed with respect to this subject will be looked at. However, also adjacent research fields will be searched to find out which methods are used in these subject areas and categorise accordingly. Not only the used techniques will be reviewed, but also, if stated, the circumstances at which they were assessed and the Measures Of Effectiveness (MOE's) that were used during the evaluation process. For instance, were the data sets synthetic of nature or acquired (real-time) in the field through monitoring sensors? If the subject of research is prediction of the traffic system; what was the prediction horizon? What were the input data and what was their aggregation level?

2.2 The state-of-the-art

An enormous amount of research is attributed to the processing stage. Incoming traffic data is interpreted as the current transport system status and predictions can be made to forecast the short-term or longer-term future transport system status. Subsequently, the transport system current and/or projected status may cause to deploy certain DTM measures.

It is beyond the scope of this chapter to review all possible studies that could be categorised into this stage. Studies on interesting subjects such as e.g. road surface performance classification / prediction (Sundin, 1995; Pillalmarri and DeCatrel, 1996; Owusu-Ababio, 1996; Roberts and Attoh-Okine, 1996) will be left aside. The focus will be on short-term traffic prediction.

Although this thesis focuses on congestion prediction, the two themes with respect to short-term traffic prediction that have been getting the most attention are travel time estimation/prediction and traffic flow prediction. This is not surprising considering that travel time and traffic flow are entities that can be measured more or less directly. Whenever 'congestion prediction' is subject of research, the problem of how to define 'congestion' is an issue. More specifically, the changes from free-flow traffic to congested traffic and from congested traffic to congestion-free traffic are difficult to identify. To solve these problems, traffic states have been translated into the famous 'Levels of Service' (LoS) as they are displayed in several editions of the Highway Capacity Manual (Transportation Research Board, 1994, 1997a, and 2000). Still, it is unclear to many professionals whether congestion kicks in at LoS D or E (D is often described as 'maximum congestion threshold', while many car drivers perceive LoS C already as congestion). Other attempts to address this problem can be found in NCHRP Report 398, Volume 1 & 2 (Transportation Research Board, 1997b and 1997c).

Another field of research that can be categorised as a data 'family' of congestion prediction is incident detection. It can be regarded as a supplement of congestion prediction, i.e. the basic assumption behind incident detection is the scheme that when detected traffic data are showing patterns that are deviating from the expected patterns, it is likely that an incident has occurred.

2.2.1 Congestion prediction

Only a few articles dealt with traffic prediction related research until the 1990's when research interest increased significantly (see also Van Arem *et al.*, 1997a). However, congestion prediction remained a virtually untouched subject. Kaysi *et al.* (1993) set up a framework for an Advanced Traveller Information System (ATIS). In this framework historical and updated Origin-Destination data with real-time data from a surveillance system were used as input to predict congestion. This may lead to scenarios where traffic control and route guidance are used to change traffic conditions. Since the framework was never implemented it was presented only at a conceptual level. The authors suggested that a Dynamic Traffic Assignment (DTA) model, fed by 3-dimensional O-D matrices - with time as the third dimension -, would be necessary to make good predictions. Two alternatives to the DTA model were given: Least Squares Estimation and the Kalman Filtering Procedure. Dougherty *et al.* (1993) described a congestion prediction research study. Motorway data were collected in the Netherlands through dual induction loops and consisted of speed, volume and occupancy at lane level. Data were aggregated to 1 minute time bins and a professional traffic manager decided whether the traffic state was congested or not. The prediction horizon was 10, 20, and 30 minutes. Only one method was used (Multi Layer Feedforward Artificial Neural Networks – MLF-ANN's) and the authors' main conclusion was that the results were promising but comparisons should be made with other methods.

Huisken and Van Maarseveen (1998) described a research design that was meant as a blueprint for the current doctoral thesis. Huisken and Coffa (2000) used motorway data that were aggregated to 1 minute time bins to predict congestion 5, 10, and 15 minutes in advance. They used time series analysis and compared the results with ANN-based models. If errors occurred they were categorised as *false alarm* (falsely predicting congestion) or *error* (failing to predict congestion) and were measured in percentage of time. The ANN technique outperformed the time series analysis technique. In Huisken (2000) two methods were compared: time series analysis and Adaptive-Network-based Fuzzy Inference Systems (ANFIS) fuzzy logic whereas the input data sets were identical to those in the study of Huisken and Coffa (2000). In this case, the two methods gave similar results. Huisken and Van Maarseveen (2000) again use the same input data sets to compare 6 different methods: Multi Linear Regression, time series analysis, Multi Layer Feedforward neural networks, Radial Basis Function neural networks, Self Organising Map neural networks, and ANFIS fuzzy logic. The performances of the methods were comparable with the exception of the SOM neural networks (results were not given due to high errors) and Multi Linear Regression that was outperformed by the other methods.

Conclusion congestion prediction research

So, it is safe to say that research on short-term congestion prediction is scarce and the subject is virtually uncovered territory, hence a justification of this research. Many aspects of congestion prediction are of interest, including the research to find out which methods are suited to develop into congestion prediction models. Since the existing research is inconclusive to determine whether certain methods provide better results than others insight into methods that are promising will be gained by having a closer look at adjacent fields of research.

2.2.2 Traffic flow prediction

Traffic intensities are usually forecasted by transforming (dual) induction loop data by means of some method into expected traffic flows. A method for the short-term prediction of traffic flow volumes based on the spectral analysis of time series was described by Nicholson and Swann (1974). Högberg (1976) used traffic counts on links in networks and non-linear regression to estimate parameters for e.g. gravity distribution models for traffic prediction. Ahmed and Cook (1977) investigated the time series analysis techniques, developed by Box and Jenkins, applied to freeway traffic volume and occupancy time series. A total of 166 data sets from three surveillance systems in Los Angeles, Minneapolis, and Detroit were used in the development of a model to provide short-term forecasts of traffic data. All of the data sets were best represented by an autoregressive integrated moving-average (ARIMA) (0,1,3) model. The moving-average parameters of the model, however, varied from location to location and over time. The ARIMA models were found to be more accurate in representing freeway time-series data, in terms of mean absolute error and mean square error, than moving-average, double-exponential smoothing, and Trigg and Leach adaptive models. Suggestions and implications for the operational use of the ARIMA model in making forecasts one time interval in advance, were also provided.

Nihan and Holmesland (1980) explored the use of time series techniques for short-term traffic volume forecasts. A data set containing volumes that were aggregated on a monthly basis of a freeway segment for the years 1968 to 1976 was used to calibrate a time series model. The resulting model was used to forecast volumes for the year 1977 which were then evaluated with actual volumes for 1977. The results of this study indicate that time series techniques can be used to develop highly accurate and inexpensive short-term forecasts. A discussion of the ways in which such models can be used to evaluate the effects of policy changes or other outside impacts was also included. Van Maarseveen (1982) used Kalman filtering based on the stochastic theory of martingales to estimate and predict macroscopic traffic flow variables from traffic counts and speed data. A study on single point short-term traffic flow forecasting by comparing seasonal ARIMA models with K-nearest neighbour forecast models was described in Smith *et al.* (2002). Data were collected on the London Orbital Motorway M25 in 1-minute time bins and then aggregated into 15-minute intervals. Evaluation was based on the Mean Absolute Percentage Error and showed that the ARIMA models outperformed the K-nearest neighbour forecast models.

Gazis and Liu (2003) applied Kalman filtering for estimating vehicle counts aggregated to 1-minute time bins for two roadway sections in tandem. Weijermars and van Berkum (2005) used cluster analysis of highway flow patterns (aggregated to 15 minute time bins) to categorise the flows into five daily flow profiles. The goal of this research, however, was to analyse the functioning of the highway traffic system rather than to manage traffic in the short-term. State-space time series (STARIMA) models were described by Kamarianakis and Prastacos (2005). The models were calibrated using 7.5-minute aggregated traffic flow data collected through loop detectors on roads that run to the city centre of Athens. The models were compared with ARIMA models, and the goodness of fit was almost identical, while the ARIMA models used 75 different parameters against only 7 parameters for the STARIMA models. Cetin and Comert (2006) use ARIMA models and extended them with the Expected Maximization (EM) algorithm (see e.g. Dempster, 1977) and the CUSUM algorithm (see e.g. Page, 1954; Schmid, 1997) to predict traffic flow speeds. Traffic data (mean speeds, occupancies, and traffic volumes) were gathered in 30-second time bins from the Interstate I-880 in California and the speed data were aggregated to 1-minute time intervals. Both extended models outperformed ordinary ARIMA models during one-step ahead predictions as measured by the Mean Square Error, the Mean Absolute Percentage Error, and the Mean Absolute Error, while the computationally demanding ARIMA-EM models gave slightly better results than the ARIMA-CUSUM models.

Cremer and Papageorgiou (1981) presented a macroscopic model that described the traffic flow on a freeway by a set of non-linear, deterministic difference equations. The model was deduced from physical and empirical considerations and contained a set of free parameters that had to be estimated using real traffic data. This identification procedure was formulated as a parameter optimisation problem that was solved by non-linear programming. In addition, the sensitivity of the model with respect to parameter changes and structural changes was investigated. Although stochastic events play a role in traffic dynamics, the results demonstrated that the validated model copes surprisingly well with real traffic behaviour.

Previous work on traffic flow prediction using supervised artificial neural networks (see e.g. Dougherty *et al.*, 1993) shows that this technique is very promising. Smith and Demetsky (1995) compared historical, data-based algorithms, with ARIMA time series analysis and back-propagation artificial neural networks. They collected 15-minute aggregated field data to estimate Root Mean Square Error, Average Absolute Error, and Average % Error. The Historical Average model and the back-propagation ANN model produced similar errors, outperforming the ARIMA model, while the ANN models slightly outperformed the Historical Average model during peak periods. Fahgri and Hua (1992) introduced the fundamental aspects of ANNs and used them to predict household trips. The outcomes, measured as Mean Square Error, were compared with linear regression and results of the ADALINE model. The latter method gave slightly better results than ANNs, but they both outperformed linear regression. Additionally, ANNs were more computer time efficient by a factor of 4. One year later, Hua and Faghri (1993) used Adaptive Resonance Theory (ART) ANNs to classify traffic patterns at roadway intersections. They used a hypothetical roadway network and a simulation model to generate 5-minute aggregated traffic volumes that were assigned to the network. The study lacked an evaluation phase hence no error measurements were given.

Ho and Ioannou (1996) used ANNs to model traffic flow in order to control it, rather then to predict future flow; evaluation was performed by determining the mean speed of simulated traffic flows on 10 road segments. A graph showed a very good fit of 'actual' and ANN generated values. In the study by Ledoux (1997) simulated data were used for urban traffic management at signalised intersections. Again, supervised artificial neural networks were used to predict vehicle queues in 1-minute time intervals and the errors were measured in vehicle numbers. Vlahogianni *et al.* (2005) use genetic algorithms to select an appropriate neural network architecture that in turn is used to predict traffic flow (3 minutes aggregated) on an urban signalised arterial road. The selected neural network showed very satisfactory results.

Unsupervised artificial neural networks (Kohonen networks) in combination with ARIMA time series were used to predict traffic flows half an hour to one and a half hour in advance on a merger of 3 motorways by using half-hour aggregated data from 3 sensors (one for each motorway) 30 kilometres upstream of the point of merger (Van Der Voort *et al.*, 1996). In this study comparisons were made with the highly complex ATHENA method (see Danech-Pajouh and Aron, 1991) and the obtained results, measured in % relative error, were comparable and almost identical.

The majority of this research only compared the performances of two different methods – if comparisons were made at all. An exception can be found in Kirby *et al.* (1997) where artificial neural networks and time series analysis were compared with, and slightly outperformed by, the ATHENA method. The data used in this study were the same as described in the study of Van Der Voort *et al.* (1996). In this study, performances were measured in % frequency of absolute percentage error.

Other exceptions are described by Huisken (2001b; 2003) and Huisken and Van Maarseveen (*under review*); these studies described comparative analyses between multiple methods. The methods used were multi linear regression, time series analysis, artificial neural networks and fuzzy logic while the input data were aggregated to 1-minute time bins. The errors were measured in Root Mean Square Error (RMSE), the Root Mean Square Error of Proportion (RMSEP), and the Absolute Relative Error Percentage (Abs. Rel. Error %). The overall conclusion of these studies was that artificial neural network models outperform the rest.

Stathopoulos and Karlaftis (2003) used a multivariate state-space method to predict urban traffic flow (3 minutes aggregated) and compared the results with those of an ARIMA (3,3) model and found the results of the state-space model to be superior to the results of the time series model. Kalman filtering with discrete wavelet decomposition is the method that was used by Xie *et al.* (2006) to come to short-term traffic flow forecasting. They compare five models (differentiated to the used level of approximation data) and found that the 3rd level approximation model gave the best results. Traffic flow data were gathered from loop detectors on Interstate 80 in Emeryville, California in 30-second time bins and the evaluation of the models was performed by comparing the Mean Absolute Percentage Error and the Variance of Absolute Percentage Error.

Based on the research described above, it was concluded that time series analysis, artificial neural networks, and linear regression seem promising candidates with for traffic flow prediction.

2.2.3 Travel time prediction

There is a wide body of research that deals with travel time estimation. Travel times could be measured using automated vehicle identification (AVI) techniques, e.g. floating car data or automated license plate recognition. These techniques are rarely used since they require large investment in roadside equipment. Currently, the bulk of available data are gathered through inductive loop detectors. Since loop detectors yield spot measurements of flow and speed, travel times must be estimated and cannot actually be measured. Dynamic travel time estimation dates back to at least 1973, when Wong and Sussman reported on comparing static and dynamic travel times between two points. Their relatively simple approach meant that the most recent observations of travel time on the network were used to update the travel time estimation. A simulation model showed that dynamic estimation outperformed static travel time estimation.

Traditionally, travel time estimation was based on time series models. In the study by Dailey (1993) cross-correlation on time series was used on 5 minute aggregated loop detector data to estimate travel times. The resulting time delay was transformed to estimate the mean speed and hence the travel time on the trajectory. Although travel time estimates were given, this article lacked an evaluation. Van Arem *et al.* (1997b) described the GERDIEN model that used inductive loop detector data aggregated to 1 minute time bins to estimate travel times and to detect incidents on a motorway network. To do so it incorporated a linear congestion detection module that combined a speed criterion with an ARMA criterion forming a vehicle mass balance. The output of the module served as input for an ARMA model that produced travel time predictions. The model was evaluated using results from a field study that contained both recurring congestion data and incidents. Incident detection evaluation was performed by measuring the False Alarm Frequency (FAF), False Alarm Rate (FAR) and Time To Detection (TTD). During the evaluation of travel time estimation the Root Mean Square Error Proportion (RMSEP) was obtained. Under normal and recurring congestion circumstances the results for travel time estimates were found to be acceptable (an RMSEP of 0.25 up to 0.40), while congestion detection could be improved.

Bhattacharjee *et al.* (2001) used Kalman filtering to capture traffic flow characteristics and additionally incorporated a Bayesian approach to update the model for route diversion behaviour in order to research the effect of travel time information on travellers' route switching behaviour. Boyce *et al.* (1993) use historical and real-time profiles to estimate travel times. Cross-correlation of induction loop data was also used by Coifman (2002) to accomplish the same result. These models were effective in their purpose of travel time estimation but were less good for travel time prediction.

Car drivers should ideally be informed of travel times that they will actually encounter. Therefore, there is a need to predict travel times, e.g. based on historic databases in combination with regression techniques and GIS (You and Kim, 2000) or event-based databases (Hounsell and Ishtiaq, 1997). Park and Rilett (1998) presented a modular artificial neural network for freeway link travel time forecasting and compare this approach with a Kalman Filtering model (Okutani and Stephanedes, 1984), the ALLSCOUT method (Hoffman and Janko, 1990), the historical travel time profile, the real-time travel time profile, and an exponential smoothing model (Chassakios and Stephanedes, 1994). Field data were aggregated into 5-minute time bins and the prediction horizon was 5, 10, 15, 20, and 25 minutes. They reported that neural networks were overall 20% more accurate at forecasting freeway link travel time in comparison with the other models using actual link travel times from an automated vehicle identification system in Houston, Texas. The same data and techniques, with the modular neural network replaced by a multi-layer feedforward neural network, were described in another study (Park and Rilett, 1999). The multi-layer feedforward neural network generated the best travel time predictions. In (Park *et al.*, 1999) the authors replaced the multi-layer feedforward neural network with a spectral basis neural network that provides the best results. Van Lint *et al.* (2002) describe research on the influence of corrupted data on travel time predictions by using state-space artificial neural network models. The authors use simulated 1-minute aggregated traffic data obtained with the simulation tool FOSIM that was heuristically scaled to field data of the A13 motorway on a typical February afternoon peak. They found out that neural network models fed with data with failure rates of up to 60% were still able to produce reasonable good results. The same models generated an error of approximately 10% when input data had no deficiencies. However, the failure rate of 60% dropped significantly when certain links, i.e. links close to bottlenecks and links too on- and off-ramps, suffer structural failure. Additional work on the same subject by the same authors (Van Lint *et al.*, 2005) presented a field data set with measured travel times included. Huisken and Van Berkum (2003) compared predicted travel times on the same A13 motorway that are generated with Multi Layer Feedforward neural networks with travel times generated by a static travel time estimator and a dynamic travel time estimator. Again, 1-minute aggregated field data was used as input data for the models and the results, measured in travel time seconds, clearly showed that the neural network model outperformed the other models. Tao *et al.* (2006) use different types of neural networks (Multi Layer Feedforward ANNs, Modular ANNs and Principal Component Analysis ANNs) to predict travel times with data including incidents. During one year, traffic data (flow, occupancy, travel times based on average speed, weather conditions) were collected from a highway corridor between Northern Virginia and Washington D.C. in 15 minutes time intervals. It was concluded by establishing the Mean Squared Error, the Normalised Mean Squared Error, and the Mean Absolute Error that the MLF ANNs showed the best overall performance, but under certain conditions other ANNs proved to be superior. The State Space Neural Networks, mentioned above in the studies by Van Lint *et al.* (2002, 2005) were compared with the instantaneous travel time estimation algorithm ASTRIVAL that was implemented on two motorway routes between Hoevelaken clover leaf and Utrecht and vice versa in the Netherlands. Data were acquired through the MONICA system resulting in 1-minute aggregated data on traffic flow, mean speed, occupancy. Mean speed and traffic flow were used to develop the SSNN models. During evaluation it was found by measuring the Mean Absolute Relative Error Percentage, the Mean Relative Error Percentage and the Standard deviation of Relative Error Percentage that the SSNN models, that were more robust with missing data, clearly outperformed the ASTRIVAL algorithm. Liu *et al.* (2006) extended the SSNN models with Kalman Filters to speed up the training phase. In their study, results measured in Mean Relative Error and Root Mean Squared Error Proportional were compared with results obtained by ordinary SSNN models and Kalman Filtered models. The results of the extended SSNN models were slightly worse than those of the ordinary SSNN models but superior to the Kalman Filtered models. However, in terms of computation time the extended model was 20 times faster.

Several artificial neural networks seem promising methods to obtain performance improvement over time series analysis for travel time prediction.

2.2.4 Incident detection

A roadway incident is an unexpected event that temporarily disrupts the flow of traffic on a segment of a roadway. Stalled vehicles, spilled debris on the road, and traffic accidents are examples of roadway incidents. When an incident occurs, there is a temporary decrease in the capacity of the roadway and if current demand exceeds this reduced capacity it results in congestion thus forming queues. The cost of delay caused by incidents is significant. Non-recurring congestion due to incidents was estimated in 1984 to cause approximately 60% of the urban freeway delay in the U.S. (Lindley, 1987). This has triggered the development of Incident Management, i.e. the timely dispatch of emergency services and incident removal crews, control and rerouting of traffic around the incident location, and provision of real-time traffic information to motorists. Therefore, effective motorway incident detection and management are key components of any potentially successful Traffic Management Centre. Incidents have to be detected as soon as possible and their nature has to be established swiftly so actions can be taken to minimise the damage. These actions depend on the nature of the incident (vehicles involved, seriousness of injuries, number of blocked lanes, etc.) and can reach from 'do nothing' to 'full scale rescue operation' where not only rescue services are notified, but also diversion routes have to be implemented and communicated to vehicle drivers so upstream traffic can be diverted.

Automatic Incident Detection (AID) systems are made up of 2 components: a traffic detection system and an incident detection algorithm. The traffic detection system usually consists of (dual) loop detectors generates traffic data such as traffic flow (intensities), vehicle speeds, and occupancy percentages, sometimes broken down into vehicle categories. The incident detection algorithm interprets traffic data and classifies it as 'no incident' or 'incident'. Loop detectors will probably serve as the primary source for incident detection for the near future. Some day this task might be carried out on a large scale by probe vehicles equipped with GSM and GPS or GNSS.

Studies of AID methodologies for motorways commenced during the 1960's in the United States. The principles of AID methodologies can be divided into 4 categories:

- *Direct comparison* between data acquired with (dual) induction loops. These are the oldest AID algorithms that compare input in a simple manner by looking at decision trees. Payne (1976) developed and tested incident detection algorithms that are based on times series and pattern recognition techniques. Attention was given to the effects of geometrics, sensor configuration and weather, and methods were developed for detecting malfunctioning sensors and for identifying the lane of an incident. The performance results were obtained with Los Angeles and Minneapolis freeway surveillance data. The research described in Payne and Knobel (1976) was based on the previous study (Payne, 1976) and described procedures for implementing software designed for incident detection and the identification of malfunctioning detectors. Guidelines were provided for choosing a basic incident detection algorithm and threshold set among the candidates offered, and procedures were described for modifying the basic algorithms to account for sensor configuration, geometrics, and other effects. Tignor and Payne (1977) presented the results of a study on the development of improved incident detection algorithms for freeway surveillance systems. A total of 10 algorithms were defined, calibrated, tested, and evaluated. False alarm levels previously experienced with incident detection algorithms were significantly reduced. The results of the improved algorithm were also presented relative to sensor configuration, geometric anomalies, and weather considerations. In Payne and Tignor (1978) the authors described incident-detection algorithms that were part of an overall freeway-traffic management system. The algorithms provided indications of the probable presence of freeway incidents by processing electronic surveillance data. They described a class of algorithms that were designed to discriminate patterns in the data peculiar to incidents. The generic structure of the algorithms is the decision tree with states, the states corresponding to distinct traffic conditions. Ways to calibrate algorithm thresholds were described and applied to the algorithms. Performance evaluations were based on traffic data from the Los Angeles system.

- *Pattern recognition* with as best known examples the California algorithms (Kahn, 1972), see also Payne *et al.* (1975) for an overview of these and other then known algorithms. Levin and Krause (1978) developed a single-feature incident-detection algorithm based on Bayesian considerations. The algorithm used both upstream and the downstream minute occupancies and historical incident information.

The historical incident data used were representative of the inner lane of the outbound Kennedy Expressway between the Chicago Loop and the Edens Expressway junction during the afternoon rush period. Mathematical expressions were developed for the distributions of the ratio of incident and incident-free data. The probabilities of incidents occurring on the outbound Kennedy were developed from available incident data. The optimal threshold to be used in the incident-detection process was determined mathematically by using Bayesian concepts. The efficiency of the algorithm were evaluated in terms of its detection rate (DR), false-alarm rate (FAR), and mean time to detect (TTD) and was compared with those of the California algorithm and two algorithms developed by Technology Services Corporation. The Bayesian algorithm compared favourably with the others for detection rate (100 percent) and false-alarm rate (0.0 percent). However, its mean time to detect was greater than that of the other algorithms by almost 2.5 minutes. A preliminary on-line evaluation comparing the Bayesian algorithm and one of the others showed no significant differences in detection rate, false-alarm rate, and mean time to detect. Tsai and Case (1979) conducted two incident-detection experiments on the Queen Elizabeth Way Freeway Surveillance and Control System in Ontario. A pattern-recognition approach was applied to improve incident-detection algorithms. By considering the true- and false-incident-alarm identification process as pattern-recognition in nature, the maximum-likelihood decision principle was applied to develop an optimum incident-duration persistence test. The false-alarm rate fell from -.09 to 9.96 percent during a nine-month field test experiment. In the second experiment a two-layer committee-machine structure achieved an 85.7 percent detection rate on 28 samples of historical incident data. Madanat *et al.* (1996) presented a freeway incident response decision-making system based on sequential hypothesis testing techniques. The primary feature of this decision-making system is that it minimises the sum of the expected losses associated with false response, non-response, and delayed responses to incidents through a dynamic programming algorithm. The results of simulation tests indicated that this algorithm performed better than typical Bayesian incident response algorithms for mean response time, false response rate (equivalent to false alarm rate), and non-response rate (an inverse of the detection rate). Sheu and Ritchie (1998) presented a new methodology for real-time detection and characterization of incidents on surface streets. The proposed automatic incident detection approach was capable of detecting incidents promptly as well as characterising incidents in terms of time-varying lane-changing fractions and queue lengths in blocked lanes, lanes blocked due to incidents, and incident duration. The primary techniques utilised in this paper included: a discrete-time, non-linear, stochastic system with boundary constraints to predict real-time lane-changing fractions and queue lengths and a pattern-recognition-based algorithm employing modified sequential probability ratio tests (MSPRT) to detect incidents. Off-line tests based on simulated as well as video-based real data were conducted to assess the performance of the proposed algorithm. The test results indicated the feasibility of achieving real-time incident detection using the proposed methodology.

- *Temporal/spatial prediction* by means of double exponential smoothing algorithms, time series analysis and Kalman filtering. Cook and Cleveland (1974) investigated the feasibility of using freeway traffic-flow data compiled by electronic surveillance and control systems for the detection of accidents and other lane blockage incidents that temporarily disrupt traffic flow. Research was conducted on 1-minute aggregated data of traffic flow and occupancy, recorded by ultrasonic presence detectors. The data acquisition took place at the John C. Lodge Freeway in Detroit. Nineteen detection algorithms, including one being used in Los Angeles, were evaluated with a sample of 50 representative afternoon peak-period incidents. The technique of exponential smoothing of traffic flow or occupancy data to detect incident-generated shock waves was found to be the most effective. This algorithm detected 42 percent of the incidents with virtually no false alarms and every incident with an 8 percent false-alarm rate. Most of the incidents were detected within 1 minute of the onset of congestion at a detector station. Algorithm effectiveness was not affected by detector spacing ranging from 445 to 1468 meters, traffic volumes from 1,200 to 2,000 vehicles per hour per lane, occupancies from 9 percent to 45 percent, precipitation, or the particular lane blocked. The algorithms could not distinguish accidents from less serious incidents, but because they directly related each incident to its impact on traffic operations their incorporation in control systems could improve system response to incidents. Dudek *et al.* (1974) proposed, developed and evaluated an automatic incident-detection model using the standard normal deviate (SND) of the control variable (energy or lane occupancy) to come to the SND algorithm. Two strategies were tested using a 3- and 5-minute database for each control variable. Strategy A required one SND value to be critical; strategy B required two successive SND values to be critical. Strategy B, using lane occupancy with a 5-minute time base, produced the best results. It detected 92 percent of the 35 incidents studied during moderate and heavy flow, with a mean detection time of 1.1 minutes and a 1 percent false-alarm rate during the peak period. Based on a limited sample size, the study indicated that the SND model was as effective as the composite model, which was considered to be the best existing model. Because the SND model does not require separate distribution curves for various traffic conditions, it may be a more attractive model for an operational system. Relationships were developed and presented that identify sensor spacing requirements for an incident-detection system using a stationary model. Ahmed and Cook (1977) presented an autoregressive integrated moving average (ARIMA) model for describing the stochastic and dynamic behaviour of freeway traffic volume and occupancy observations. The model was applied to the detection of freeway capacity-reducing incidents through the sudden and pulsed changes they generate in traffic stream described with time series data. An incident is detected if the observed value of traffic occupancy lies outside the 95%-probability limits (two standard deviation errors away from the corresponding forecast point). The developed ARIMA occupancy algorithm proved to generate superior results in comparison to the exponential and the California algorithms in terms of detection rate, false alarm rate, and mean time lag to detection. The analysis was based on surveillance data recorded at the Los Angeles, Minneapolis, and Detroit freeway systems during the afternoon peak periods. Willsky *et al.* (1980) discussed the approach to the detection of incidents on freeways. The techniques were based on the use of a macroscopic dynamic model describing the evolution of spatial-average traffic variables (velocities, flows, and densities) over sections of the freeway. This model was then developed into two incident detection algorithms based on the multiple model and generalised likelihood ratio techniques. A description is given of a new and very simple system for processing raw data from presence-type vehicle detectors to produce estimates of the aggregate variables, which are then in turn used as the input variables to the incident detection algorithms. Results were based on simulated data. Ahmed and Cook (1982) used their previously developed ARIMA model (see Ahmed and Cook, 1977) to describe the dynamic and stochastic character of freeway traffic variables. This model was used to provide short-term forecasts of traffic occupancies and the associated 95%-probability limits. An incident was detected if the observed occupancy value lies outside the probability limits of the corresponding point forecast. A total of 1692 minutes of occupancy observations associated with 50 traffic incidents that took place on the Lodge Freeway in Detroit were used in evaluating the algorithm performance. The algorithm detected all 50 incidents. The resulting false-alarm rate was 2.6 percent when constant parameters of the ARIMA model were used and it decreases to 1.4 percent with variable-parameter estimates. Furthermore, the average time lag to detection when constant- and variable-parameter estimates were used was 0.58 minutes and 0.39 minutes, respectively. Balke *et al.* (1996) described a pilot study to test the feasibility of using probe-provided travel time information to detect freeway incidents. As part of the pilot study, 200 commuters equipped with cellular telephones were used to collect travel time and incident information from three roads, the I-45, the Hardy Toll Road, and US-59, on the north side of Houston, TX. Historical travel time patterns were developed for each link using data from known incident-free conditions. The statistical principle of standard normal deviates was applied to 11 months of data to determine when a probe travel time exceeded the expected travel time under incident-free conditions. This approach resulted in detection rates that were lower and false alarm rates that were higher than those reportedly produced by other incident detection algorithms. However, the study illustrated that some level of incident detection could be achieved using travel time information provided by probe vehicles. Because of limitations in the data, it was not possible to determine the number of incidents that were not detected by the system or the times to detection for known incident conditions. Teng and Qi (2003) described models based on traffic flows that were transformed using the wavelet technique (somewhat comparable with Fourier Analysis). They compared these models with Probabilistic ANNs, MLF ANNs, RBF ANNs, the California algorithm, and low-pass filtering algorithms. Occupancy data were acquired in 30-second time bins from the California Interstate I-880 in order to calibrate the models. By comparing the False Alarm Rate and the Detection Rate it was concluded that the wavelet models outperformed the other models.

- *Data processing* using catastrophe theory (the McMasters algorithm), and using Artificial Intelligence (AI). Persaud and Hall (1989) analysed 30-second aggregated data on flows, occupancies, and average speeds of freeway areas near bottlenecks caused by incidents. One of the key areas in which the catastrophe theory model fits the data better than conventional models is with regard to the transitions to and from congested areas upstream of incidents. The data suggested that such transitions were characterised by a minor change in occupancy and flow, but by a sharp change in speed. Based on these results, the authors suggested the catastrophe theory model, developed by using flow-occupancy-speed patterns, for freeway incident detection purposes. In 1993, Hall *et al.* reported an improvement of the scheme for incident detection reported in Persaud and Hall (1989). The improved incident detection scheme has gone through three levels of testing where data from the Freeway Traffic Management System on the Queen Elizabeth Way in Ontario were used. An improved scheme that could recognise and then ignore recurrent congestion and that could identify incidents that occurred within recurrent congestion was developed and tested off-line. The data used for this stage consisted of 39 days from early summer 1990. The algorithm was then installed on-line, and its results were reported to a file instead of to the system operator. After a period of initial testing and revision to the algorithm and parameters, a major on-line test was conducted during 64 normal weekdays from March 12 to June 18, 1992. The detection rate of the algorithm was 68% (19 of 28 incidents). For the 19 incidents, the algorithm time to detection averaged 2.1 minutes after the time recorded in the operator's log; the median time to detection was 1 minute later than for the operator. The false alarm rate was 20 during the 64 days of testing. Stephanedes and Chassiakos (1993) used a low pass filtering technique that reduced the likelihood of false alarms that occur during short duration of traffic disturbances by smoothing detector occupancies. Temporal smoothing was performed by the statistical mean or median of a data window moved over time. The algorithm used the smoothed spatial occupancy difference between detector stations, and detected an incident when the difference changes significantly in a short time period. The proposed algorithm and a set of existing algorithms were assessed with traffic and incident data from I-35W in Minneapolis. Test results, expressed in terms of detection rate and false alarm rates, demonstrated the improved performance of the new algorithm over previous algorithms. The most commonly used AI techniques in incident detection are Artificial Neural Networks (ANNs). Ritchie and Cheu (1993) hypothesised that spatial and temporal traffic patterns can be recognised and classified by an artificial neural network, and presented an investigation of such models for the automated detection of lane-blocking incidents in a one-mile section of urban freeway. The artificial neural network was trained with data obtained from a microscopic freeway traffic simulation model that was specially calibrated for the actual freeway test section. The neural network first classified the traffic state of the freeway section into either 'incident-free' or 'incident' conditions in every 30-second interval. The changes in traffic state from incident-free to incident conditions were then used to trigger an incident alarm. Based on the results of an off-line test using simulated data, and comparisons with the well known California incident-detection algorithm and the modified McMaster algorithm, the results suggested that neural network models have the potential to achieve significant improvements in incident-detection performance. Cheu and Ritchie (1995) developed three types of neural network models, i.e. the multi-layer feedforward (MLF), the self-organizing feature map (SOFM) and adaptive resonance theory 2 (ART2), to classify traffic surveillance data obtained from loop detectors. The objective of using the classified output was to detect lane-blocking freeway incidents. The models were developed with simulation data from a study site and tested with both simulation and field data at the same site. The MLF was found to have the highest potential, among the three ANNs, to achieve a better incident detection performance. The MLF was also tested with limited field data collected from three other freeway locations to explore its transferability. The results and analyses with data from the study site as well as the three test sites showed that the MLF consistently detected most of the lane-blocking incidents and typically gave a false alarm rate lower than the California, McMaster and Minnesota algorithms that were in operation at that time. Dia and Rose (1997) discussed a multi-layer feed-forward (MLF) neural network incident detection model that was developed and evaluated using field data. The model described in the study was trained and tested on a real-world data set of 100 incidents. The model used speed, flow and occupancy data measured at dual stations, averaged across all lanes and only from time interval *t*. The off-line performance of the model was reported under both incident and non-incident conditions. The incident detection performance of the model was reported based on a validation-test data set of 40 incidents that were independent of the 60 incidents used for training. The false alarm rates of the model were evaluated based on non-incident data that were collected from a freeway section that was video-taped for a period of 33 days. A comparative evaluation between the neural network model and the incident detection model in operation on Melbourne's freeways was also presented. The results of the comparative performance evaluation clearly demonstrated the substantial improvement in incident detection performance obtained by the neural network model. The paper also presented additional results that demonstrate how improvements in model performance can be achieved using variable decision thresholds. Finally, the model’s fault-tolerance under conditions of corrupt or missing data was investigated and the impact of loop detector failure on the performance of the trained model was evaluated and discussed. The reported results provided a comprehensive evaluation of the developed model and confirm that neural network models can provide fast and reliable incident detection on freeways. Ivan (1997) developed four artificial neural networks for detecting incidents on signalised arterial roads using multiple data sources. Two incident detection algorithms processed unique data sources separately: inductive loop detectors, and travel times were collected from vehicle probes travelling through the street network. The networks then combined the algorithm inferences about traffic conditions to identify highway links on which incidents were occurring. The four networks considered the following inputs: (1) the two algorithm output values alone; (2) a weighted geometric sum of previous network output values; (3) algorithm scores from links immediately upstream and downstream of the subject link; and (4) weighted geometric sums of previous input values. The four representations were trained as feed-forward networks using error back propagation. Time series inputs were represented with extra processing units and fixed weight connections. The networks were trained with simulated traffic data in order to control traffic demand, operation and incident conditions. Each network was trained until performance began to degrade on a separate data set (that was not used during the training phase). Adding the output time series permitted two of the 24 incidents to be detected sooner than with the network that did not include this input. Similarly, using information from adjacent links in time series permitted all of the incidents to be detected by at least the third time period. Fuzzy Logic neural networks were proposed by Xu *et al.* (1998) to develop a scheme that consisted of two stages. First, a real-time adaptive on-line procedure was used to extract the significant components of traffic states, i.e. average velocity and density. Second, a neural network called Fuzzy CMAC (Cerebellar Arithmetic Computer) was used to identify traffic incidents. The authors state that Fuzzy CMAC is an ideal candidate for the purpose of incident detection because the Fuzzy CMAC learning structure is a creative use of fuzzy logic and CMAC based neural networks. Expert knowledge in terms of linguistic rules can be incorporated into the design. Additionally, the learning process was well suited for real-time application since the training process is an order of magnitude faster than that of conventional artificial neural networks. Finally, the Fuzzy CMAC can be implemented in high speed, highly parallel hardware. The goal of the research was threefold: a good traffic incident detection system will help drivers to select an optimum route, the system will be able to provide information for efficient dispatching of emergency services, and the system will provide accurate knowledge of existing traffic conditions in order to guide effective on-line traffic control. Ishak and Al-Deek (1998) used Fuzzy ART neural networks to develop models for incident detection on freeways. Fuzzy ART was capable of fast, stable learning of recognition categories. The Fuzzy ART model was trained with traffic patterns that were represented by 30-second loop-detector data of occupancy, speed, or a combination of both. Traffic patterns observed at the incident time and location were mapped to a group of categories. Each incident category mapped incidents with similar traffic pattern characteristics, which were affected by the type and severity of the incident and the prevailing traffic conditions. Detection rate and false alarm rate were used to measure the performance of the Fuzzy ART algorithm. To reduce the false alarm rate that results from occasional misclassification of traffic patterns, a persistence time period of 3 minutes was arbitrarily selected. The algorithm performance improves when the temporal size of traffic patterns increases from one to two 30-second periods for all traffic parameters. The authors reported that speed patterns produced better results than occupancy patterns. However, when combined, occupancy-speed patterns produced the best results. When compared with California algorithms 7 and 8, the Fuzzy ART model produced better performances. A Fuzzy-Expert model was used by Lin and Chang (1998) to detect incidents. They used the software package FRESIM to generate a simulated data set and subsequently calculated the Detection Rate, the False Alarm Rate and the

Detection Time. No comparisons with other models were made. Khan and Ritchie (1998) developed a discriminant analysis-based classifier, a Bayes classifier and a time series model and two ANN models (a modular ANN and a MLF ANN) to detect incidents on urban surface street networks. Four urban data sets were acquired, two field data sets through inductive loops in Los Angeles and in Anaheim (California). Additionally, simulation data sets were gathered based on the networks of these cities. Based on establishing the False Alarm Rate, Detection Rate, and Time To Detect, the ANN models outperformed the other models. Srinivasan *et al.* (2000) developed hybrid Fuzzy – Genetic Algorithm models and compared the resulting performances with an ANN model, California no. 8 algorithm, the McMaster algorithm, and the Minnesota algorithm. Lane specific volume and occupancy data were gathered in 30-second time bins on a section of the expressway SR-91 in California (westbound). By comparing the False Alarm Rate and the Detection Rate it was concluded that the hybrid and the ANN models outperformed the remaining ones. The hybrid algorithm had a shorter Time To Detect and a higher Detection Rate than the ANN model, however, the False Alarm Rate of the hybrid algorithm was higher. Sheu (2002, 2004) presented a method that was constructed primarily on the basis of the fuzzy clustering theories to identify automatically freeway incidents. The proposed approach was capable of distinguishing the time-varying patterns of incident-induced traffic states from the patterns of incident-free traffic states, and characterising incidents with respect to the onset and end time steps of incidents, incident location, the temporal and spatial change patterns of incident-related traffic variables in response to the impacts of incidents on freeway traffic flows in real time. Lane traffic count and density were the two major types of input data, acquired with point detectors. Based on the spatial and temporal relationships of the collected raw traffic data, several time-varying state variables were defined, and then evaluated quantitatively and qualitatively to determine the decision variables used for real-time incident characterization. Utilising the specified decision variables, the proposed fuzzy clustering-based algorithm executed recurrently three major procedures: first it identified traffic flow conditions, then it recognised incident occurrence, and finally it characterised the identified incident. The data used in the study were generated from the CORSIM traffic simulator. Preliminary test results indicated that the proposed approach was promising, and could be integrated with any real-time incident detection technologies. Error measurements are given for detection rate, false alarm rate, time to detect and Accuracy of Incident Characterisation (AIC), which was defined as 'the number of incidents detected with correct characterisation' divided by 'the total number of incidents'. Messai *et al.* (2005) used ANNs to extract flow-density relations from real traffic data. Petri

Nets subsequently categorised speed/flow data points and classified them as incident if they were too far from the fundamental diagram. Calibration data were gathered in Nancy, France, but no comparison with other models was made. Srinivasan *et al.* (2005) compared three different artificial neural network based models to detect incidents. Multi Linear Feedforward ANN's outperformed Basic Probabilistic Neural Networks and Constructive Probabilistic Neural Networks, given measurements of Detection Rate, False Alarm Rate and Time To Detect. The incident database that was used during the first phase was based on simulated traffic flow on the Ayer Rajah Expressway in Singapore. During the second phase the transferability was checked by recalibrating the models using data gathered in 30-second time bins from the I-880 (California). During the second phase, the CPNN model showed the best results.

Algorithms that use thresholds, as described in the 1st and 2nd category, try to detect incidents by checking out the most recent group of patterns gathered by loop detectors. However, by ignoring temporal data these types of algorithms are unable to filter random fluctuations and are therefore sensible to the geometry of the road and traffic conditions. The calibration of the algorithms is subsequently a time-consuming and often tedious job.

Dynamic algorithms that use multiple temporal observations (time series), as described in the 3rd category, should be more robust. Unfortunately, the algorithms are based on the questionable assumption that during normal traffic conditions intensities / occupancies can be regarded as a linear function of intensities / occupancies of the present and recent past. An alarm is usually issued if acquired traffic data differs significantly from predicted data. In reality, traffic flows are determined by traffic conditions upstream or downstream depending on the level of congestion, i.e. traffic intensities are non-linear in areas where congestion is growing or the traffic flow is regenerating. This means that these types of algorithms can identify transitions between congestion and free-flow traffic but also that the algorithms cannot differentiate between recurrent and non-recurrent congestion.

Algorithms that fall in the last category generally produce the best results (again, see Cheu and Ritchie, 1995). The main problem of these algorithms is their huge amount of parameters that are sensible to the geometry of the road and traffic conditions. Consequently, their usability on other locations is minimal due to time-consuming recalibration. However, attempts are made to minimise these problems (Abdulhai and Ritchie, 1997 & 1999). The authors introduced an algorithm with potential for enhanced performance. The algorithm was a modified form of the Bayesian-based Probabilistic Neural Network

(PNN) that utilised the concept of statistical distance. The study provided a detailed definition of the attributes and capabilities that a potentially universal freeway incident detection framework should possess. Then the authors discussed the training and testing phase of the PNN which were followed by the evaluation phase of the PNN relative to the universality template that was defined. In addition to a large set of simulated incidents, large real incident databases from the I-880 freeway in California and the I-35W in Minnesota were used to comparatively evaluate the performance and transferability of different algorithms, including the PNN. Experimental results indicated that the new PNN-based algorithm was competitive with the Multi Layer Feed Forward (MLF) architecture, which was found in previous studies to yield superior incident detection performance, while being significantly faster to train. In addition, results also point to the possibility of utilising the real-time learning capability of the PNN architecture to produce a transferable incident detection algorithm without the need for explicit off-line retraining in the new site. The PNN has been found to improve in performance with time in service as it retrains itself on captured incident data, verified by the Traffic Management Centre (TMC) operator. The overall PNN-based framework looked promising with respect to universality requirements.

There is research interest in developing incident managing strategies incorporating journey time prediction in incident conditions (Janko, 1989; Sing and Wirasinghe, 1994; Van Vuren and Leonard, 1994), say, a unification of paragraph 2.2.3 and the current one. Hounsell and Ishtiaq (1997) used simulated data (5-minute aggregated) to predict journey times and error measurement was performed by comparing predicted and simulated journey times as Mean Error (ME), Mean Absolute Error (MAE) Mean Absolute Percentage Error (MAPE). Incidents can not be predicted so car drivers will not know for certain which route will be the fastest from origin to destination, however, the proposed strategies try to provide the car driver (e.g. by means of a navigation system) with the fastest alternative route once an incident has occurred and has been detected on the route that she or he initially chose. Stathopoulos and Karlaftis (2003) presented a study on developing flexible and explicitly multivariate time-series state space models using urban area loop detector data. Data were acquired from urban arterial streets near downtown Athens and consisted of 3-minute aggregated volume measurements. The models were developed using data from upstream detectors as input to improve on the predictions of downstream locations. The results suggested that different model specifications were appropriate for different time periods of the day. Further, it also appeared that the use of multivariate state space models improved on the prediction accuracy over univariate time series ones. Sheu *et al.* (2004) presented a discrete non-linear stochastic model to characterise the time-varying relationships of specified lane traffic states under the condition of lane-blocking incidents on surface streets. The proposed stochastic model was composed of recursive equations, measurement equations, delay-aggregation equations, and boundary constraints. Additionally, a recursive estimation algorithm was developed for real-time prediction of the specified time-varying lane traffic states. The proposed method is tested with simulated data generated by the Paramics software package. Preliminary tests indicated the capability of the proposed method to estimate incident effects on surface street traffic congestion in real time. The authors expect that the method also can provide real-time incident-related traffic information with benefits both for understanding the impact of incidents on non-recurrent traffic congestion of surface streets, and for developing advanced incident-responsive traffic control and management technologies.

With time the methods that are used to detect incidents become increasingly complex and able to capture non-linear phenomena. The methods that are able to model non-linearity seem to outperform linear models. However, state-space linear models seem to produce acceptable results and have the advantage that they do not classify as “black box” techniques. State-space methods as well as methods that are able to model non-linearity like artificial neural networks and fuzzy logic should be tested for modelling congestion prediction.

2.2.5 Overview

When reviewing literature on traffic prediction and incident detection it is clear that this concerns the processing stage. Although the immediate goal may seem somewhat different at first sight, the ultimate goals of the subjects researched in section 2.2 are the same: more efficient use of the current infrastructure by selecting appropriate DTM measures. In case a certain route suffers from an incident, rerouting measures and incident management can quickly come to action. When congestion is about to set in at a certain point, measures can be taken (e.g. traffic calming) to postpone or omit a time consuming traffic flow regeneration and to inform travellers on that use the traffic system to increase the reliability on the current and near-future state of that traffic system.

Based on the research described, a selection of methods that will be used has to be made to develop models for short-term congestion prediction. Obviously, the selected methods should have the potential of delivering reasonable to good results, at least according to the researchers who performed the reviewed studies. Therefore, the selected methods are: Multi Linear Regression, ARMA Time Series Analysis, MLF neural networks, RBF neural networks, State-Space (also known as Elman) neural networks, SOM neural networks, and ANFIS fuzzy logic.

Field data will be collected through monitoring sensors and the prediction horizon will be up to 30 minutes. As measures of effectiveness the Mean Absolute Percentage Error; both False Alarm (the model wrongly predicts congestion) as well as Error (the model fails to predict congestion) will be used.

Since previous research on short-term congestion prediction is very limited, there is need for a comparative analysis on methods used for model development. Which method or methods can be developed into models that will generate the best congestion predictions? This question leads us to the research approach specification.

2.3 Research approach specification

We now have described the state-of-the-art with respect to short-term traffic prediction and made a selection of methods that will be used to develop models. Chapter 1 ended with the research question:

> *Which of the methods gives the best congestion predictions on motorways within the short-term horizon and under what circumstances are these predictions achieved?*

Consequently, in the light of the state-of-the-art with respect to current research described in section 2.2 this research question has to be made more specific; it needs to be extended with more details by means of definitions of the terms used.

- *Method*: the methods that are used are: the Naïve method, Multi Linear Regression (MLR), Auto Regression Moving Average (ARMA) Time Series Analysis, Multi Layer Feed-forward (MLF) neural networks, Radial Basic Function (RBF) neural networks, Elman (State-Space) neural networks, Self Organising Map (SOM) neural networks and Fuzzy Logic (FL). These methods are used to develop models.

- *Congestion*: the MoniCa databases posses a congestion indicator entry. The indicator flag is switched 'on' if 5 vehicles subsequently pass an induction loop detector with a speed below 35 km/h. It is turned 'off' again when 5 vehicles subsequently pass the detector with a speed over 50 km/h.

- *Performance*: the Measures Of Effectiveness (MOE's) or performances of the methods are established by estimating the False Alarm percentage and the Error percentage; the combination of these

MOE's add up to the total (absolute) error percentage. The performance measurements are described in more details, with accompanying formulas, in the results chapter (chapter 8).

- *Short-term horizon*: as mentioned above, the short-term horizon is here defined as the 5 – 30 minutes look-ahead period.

- *Circumstances*: the environment at which the models are tested. Many variables can be used to describe the circumstances that influence the performances of the methods. These variables include environmental variables, pre-processing variables, and model variables and will be explained in more detail in the next section.

The main research question will be divided into postulated hypotheses in chapter 5. Before these hypotheses are given first the methods that were used (chapter 3) and the data sets that were acquired (chapter 4) have to be described.

2.4 Research approach

This section describes the design of the research project in order to answer the main research question. It specifies the general pragmatic framework of the research by taking into account which additional variables to the ones named in the main research questions can possibly influence the method's performance results and how to minimise their contribution to the results.

The influence of the used methods will be analysed by collecting two data sets on two different geographical sites. The data sets will be acquired on sites with bottlenecks that are virtually uninfluenced by other bottlenecks.

To make sure the complexity of the geographical sites do not differ too much, they have to satisfy most of the following constraints (ordered according to importance):

1. The sites must have the possibility of retrieving data.
2. The sites have to include a bottleneck.
3. The sites have to suffer from congestion, but not on a day-to-day basis.
4. The sites may not differ much in the infrastructure architecture.
5. The sites should not differ much in the number of lanes.
6. The sites have to suffer from the same kind of congestion.

The total research scheme can be displayed as in figure 1.2:

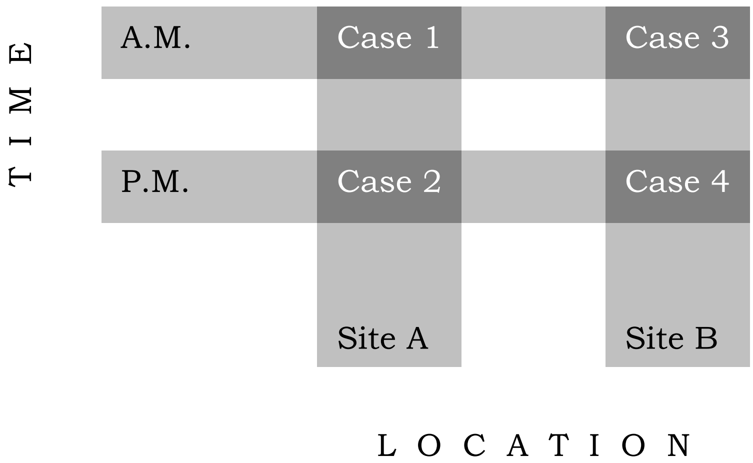

Figure 2.1: *The research scheme*

Figure 1.3 displays the process of information flow. It also shows the identified variables and where they might influence the information flow process and thus subsequently influence the method's performances.

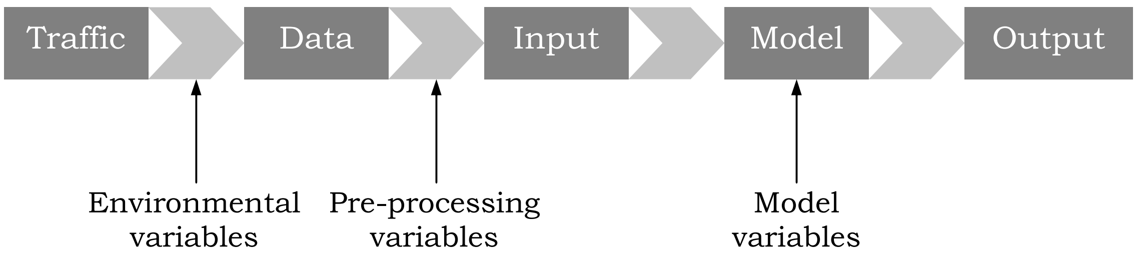

Figure 2.2: *The information flow process*

The inventory of variables:
Environmental variables: These are variables that indirectly influence the traffic flow. The identified variables are:
- Climate variables (e.g. rain, wind, snow, hailstones, fog, visibility);
- Time variables (e.g. time of day, day of week, month of year);
- Driving behaviour variables (e.g. distance headway, acceleration time, braking time, anticipation, aggressiveness, hurry);
- Incidents.

Pre-processing variables: These are variables that can be measured by (double) loop inductor sensors. The identified variables are:
- Occupancy;
- Intensity (or volume);
- Vehicle length;
- Mean speed (aggregated data);
- Standard deviation of mean speed (aggregated data);
- Aggregation level;
- Infrastructure network complexity (data aggregation site).

Model variables: These are variables that are model dependent. Since all models are data-driven this means that the model variables depend on the acquired data sets. More information can be found in the next chapter that provides an overview of the methods that were used.

The main research question tries to find out which method that is used to forecast congestion within the short-term horizon produces the best performance. The variables that are important are all pre-processing and model variables. However, the acquired data sets have all been influences by the environmental variables. To minimise their influence the acquisition of the data sets has to be handled carefully.

Since the environmental variables cannot be controlled, they have to be determined as good as possible. If extreme environmental variable values with regard to 'normal conditions' (for the time of the year when the set is acquired) appear and thus disproportionately might influence the data set, the data that was influenced has to be expelled. Unfortunately, the driver behaviour variables cannot be monitored because they act on micro level, so the assumption that driver behaviour does not fluctuate much has to be made. Time variables actually do not influence the data set but might play a role during the analysis phase as an explanatory factor. This leaves extreme climate variable values and incidents as reasons for data removal.

When a data set is collected it has to be checked on extreme climate variable values and incidents. After removing corrupted data the filtered data set can be used to analyse the method's performances with regard to the particular infrastructure section of data gathering.

The issue of transferability will be looked upon by gathering data on different geographical spots that have comparable infrastructure network architecture (both of them cloverleaf).

CHAPTER 3

Methods

"It is common sense to take a method and try it.
If it fails, admit it frankly and try another.
But above all, try something."

Franklin D. Roosevelt

3.1 Introduction

The section reports on the methods that will be used to build models of which their ability to predict adequately congestion in the short-term will be assessed. The reasons for choosing these methods have been described in the previous section, i.e. they are the most commonly used or promising methods when it comes to traffic prediction modelling. Next to deterministic methods like Multi Linear Regression and time series analysis, soft-computing techniques have been chosen. Soft-computing is a practical alternative for solving computationally complex and mathematically intractable problems. The reason that lies behind this understanding is the fact that through the use of soft-computing techniques, one can easily combine the natural system dynamics and an intelligent machine. In this respect, the intelligence stems from the combination of an expert's knowledge and massively parallel and adaptive data processing architecture of the computationally intelligent approach adopted. The most popular members of the soft-computing methods are artificial neural networks and fuzzy logic. This section provides a short description of the basic assumptions and properties underlying each of the chosen methods.

The methods that are chosen are: Multi Linear Regression, Auto Regression Moving Average time series analysis, Artificial Neural Networks (four different neural networks: Multi Layer Feed-forward neural networks, Radial Basis Function neural network, Elman neural networks, and Self-Organising Map neural networks), and Fuzzy Logic (the Adaptive-Network-based Fuzzy Inference Systems variant). To get a better grasp of the impact of the prediction results of the methods, the results are also compared with the results of the 'do nothing' scheme; the naïve method.

The above-mentioned methods have in common that they all can be described as data driven methods, meaning that the development of the models is heavily dependent on the data set it has to process and that will be used to calibrate and/or train the models and validate them during the analysis phase. In order to compare the prediction performances of the methods they should provide results in the same quantities. The chosen quantity is the binary congestion indicator ('congestion' or 'no congestion'). This indicator has advantages during the pre-processing phase because the congestion indicator is already incorporated in the acquired field data set. The congestion indicator is used as a target for each methodology and will be used to determine the performances of the methods during the validation stage.

3.2 The naïve method

The first method cannot be qualified as a sophisticated prediction method; it can better be described as a 'do-nothing-scenario' method. So, this rather naïve method assumes that during the period during which predictions can confidently be made (i.e. the prediction horizon) the state of the (transport) system at a particular point (with regard to congestion) is stationary. In other words: this method predicts that observation Y at time t will remain unchanged during the look-ahead period and therefore is equal to observation Y at time $t = t + T$, with T being the prediction horizon. Mathematically, the naïve method can be noted as:

$$Y_{t+T} = Y_t \tag{3.1}$$

Traffic Engineering viewpoint of using the naïve method

The naïve method is used as a method of reference. If models based on certain methods are outperformed by models that are based on the naïve method, it is fair to say that the former models do not posses added value with regard to congestion prediction. The performances of naïve models can also be looked upon as thresholds that other models have to pass before their performance can be characterised as 'significant'. Naïve models are deterministic models.

3.3 Multi Linear Regression

Multi-Linear Regression (MLR) is a fairly simple method to describe observations Y that are linearly depending on (explanatory) variables θ and white noise ν with mean zero and variance σ^2 (Gaussian disturbances) and can be mathematically noted as (Bickel and Jackson, 1977):

$$Y_i = \theta_0 + c_{1i} \cdot \theta_1 + c_{2i} \cdot \theta_2 + \cdots + c_{ki} \cdot \theta_k + \nu_i \tag{3.2}$$

The noise with mean zero is not taken into account so (3.2) can be rewritten as:

$$\theta \cdot C = Y \tag{3.3}$$

and c can be found by:

$$C = \left(\theta^T \cdot \theta\right)^{-1} \cdot \theta^T \cdot Y \tag{3.4}$$

With parameters C determined, they can then be used to estimate new observations Y given new variables θ. MLR is the most common regression technique and is usually used to model linear systems.

Traffic Engineering viewpoint of using the MLR method

The models built with the MLR method should show good results if the output variable (i.e. congestion or no congestion over a prediction period of 5, 10, 15, 20, 25, or 30 minutes) is linear depending on the explanatory variables (mean speed, standard deviation of mean speed, traffic intensity, occupancy, etc.); see chapter 7 'model development'. The advantage of the use of the MLR method is the explanatory power of the models. The goodness of fit of MLR models can be established by measuring the R-square value. MLR models are deterministic models.

3.4 Auto Regression Moving Average time series analysis

The purpose of time series analysis is to obtain insight into the structure of the phenomenon that generates the time series. Generally the phenomenon is modelled as a stochastic process. The time series then is a realisation of the stochastic process. Depending on whether the observations are recorded at discrete instants only (with equivalent intervals) or continuously the time series is referred to as a discrete or a continuous time series. The focus will be on discrete time series.

An important parametric family of (stationary) time series are the autoregressive moving average (ARMA) time series. The ARMA time series analysis method (Box and Jenkins, 1976) is widely used as a time dependent prediction method and is defined by an Auto Regression (AR) process and a Moving Average (MA) process.

The Auto Regressive time series of order p, AR(p), can be written as:

$$X_t = a_1 \cdot X_{t-1} + a_2 \cdot X_{t-2} + \ldots + a_p \cdot X_{t-p} + \varepsilon_t \tag{3.5}$$

for $t = p, p + 1, \ldots$ The constant coefficients $a_1, a_2, \ldots, a_p$ are real numbers and ε_t is stationary white noise with mean μ and standard deviation σ. The process is called auto-regressive because the value of the process at time t, in addition to a purely random component, depends on the p immediate past values of the process itself. A special case is the AR(1) scheme that is often called a Markov scheme.

The Moving Average time series of order q, MA(q), can be written as:

$$X_t = b_0 \cdot \varepsilon_t + b_1 \cdot \varepsilon_{t-1} + \ldots + b_q \cdot \varepsilon_{t-q} \tag{3.6}$$

for $t = q,\ q + 1, \ldots$ The constant coefficients b_0, b_1, …, b_q are real numbers and ε_t is white noise with mean μ and variance σ^2. The value X_t of the process at time t is the weighted sum of the q + 1 immediately preceding values of the white noise process ε_t and hence explains the name.

Given F observations X_0, X_1, …, X_{F-1}, ARMA(p,q) time series processes can be written as a combination of (3.5) and (3.6) in the form:

$$X_t = \mu + a_1 \cdot X_{t-1} + a_2 \cdot X_{t-2} + \ldots + a_p \cdot X_{t-p} + b_0 \cdot \varepsilon_t + b_1 \cdot \varepsilon_{t-1} + \ldots + b_q \cdot \varepsilon_{t-q} \tag{3.7}$$

for $t = p,\ p + 1, \ldots$ and with ε_t is white noise with mean zero and variance σ^2.

The parameters μ, a_1, a_2, …, a_p, b_0, b_1, …, b_q, and σ^2 can be estimated by deriving least squares and maximum likelihood estimators. Formula (3.7) can be rewritten as:

$$R \cdot X = M \cdot \varepsilon + P \cdot X^0 + \mu \cdot I, \quad X = \begin{bmatrix} X_p \\ X_{p+1} \\ \cdots \\ X_{F-1} \end{bmatrix} \quad X^0 = \begin{bmatrix} X_0 \\ X_1 \\ \cdots \\ X_{p-1} \end{bmatrix} \quad \varepsilon = \begin{bmatrix} \varepsilon_{p-q} \\ \varepsilon_{p-q+1} \\ \cdots \\ \varepsilon_{F-1} \end{bmatrix} \tag{3.8}$$

with R, M, and P representing matrices containing the a and b parameters and I being the unity vector. Least squares estimation is obtained by minimising (3.8) and maximum likelihood estimation is obtained by maximising (3.8), see Hamilton (1994); a short description of Least squares estimation and Maximum likelihood estimation is given in appendix C. ARMA time series analysis is predominantly used to model processes that can be measured consistently (discrete) in time.

Traffic Engineering viewpoint of using the ARMA method

AutoRegressive models and Moving Average models are calibrated on a sequence of data points measured at successive times, (usually) spaced at uniform time intervals. They depend linearly on previous data points and are able to capture historical patterns. So, the models use previously witnessed patterns in time to predict future outcomes. Therefore, time series analysis should be able to provide acceptable to good results under recurrent congestion circumstances. ARMA time series analysis models are deterministic models.

3.5 Artificial Neural Networks

Artificial Neural Networks (ANNs) are based upon biological neural networks - like the human brain - by mimicking their architectural structure and information processing in a simplified manner. They both consist of building blocks or processing elements called neurons that are highly interconnected making the networks parallel information-processing systems. Although the artificial neural networks are a rudimentary imitation of biological ones they are to some extend capable of tasks such as pattern recognition, perception and motor control, which are considered poorly performed and highly processor time inefficient by conventional linear processing, whereas they seem to be done with ease by e.g. the human brain. Neural networks are also known to be robust and to have the capability to capture highly non-linear mappings between input and output.

In principle, ANNs can compute any computable function, i.e., they can do everything a normal digital computer can do (Valiant, 1988; Sarle, 1997; Siegelmann and Sontag, 1999; Sima and Orponen, 2001).

Practical applications of ANNs most often employ “supervised learning” for the computer using ANNs. For supervised learning, one must provide training data that includes both the inputs and the desired results (the target values). After successful training, input data can be presented alone to the ANN (i.e. input data without the desired results), and the ANN will compute output values that approximate the desired results. However, for training to be successful, lots of training data and lots of computer time are needed to do the training. In many applications, such as image and text processing, a lot of work will have to be done to select appropriate input data and to code the data as numeric values (the pre-processing phase).

In practice, ANNs are especially useful for classification and function approximation/mapping problems which are tolerant of some imprecision, which have plenty of training data available, but to which hard and fast rules (such as those that might be used in an expert system) cannot easily be applied. Almost any finite-dimensional vector function on a compact set can be approximated to arbitrary precision by feed-forward ANNs (which are the type most often used in practical applications) provided one has enough data and enough computing resources at hand.

To be more specific, feed-forward networks with a single hidden layer and trained by least-squares are statistically consistent estimators of arbitrary square-integrable regression functions under certain practically-satisfiable assumptions regarding sampling, target noise, number of hidden units, size of weights, and form of hidden-unit activation function (White, 1990). Such networks can also be trained as statistically consistent estimators of derivatives of regression functions (White and Gallant, 1992). Feed-forward networks with a single hidden layer using threshold or sigmoid activation functions are universally consistent estimators of binary classifications (Faragó and Lugosi, 1993; Lugosi and Zeger 1995; Devroye *et al.*, 1996) under similar assumptions. So, these results are stronger than the universal approximation theorems that merely show the existence of weights for arbitrarily accurate approximations. However, it is important to understand that there are no methods for training ANNs that can magically create information that is not contained in the training data.

Feed-forward ANNs are restricted to finite-dimensional input and output spaces. Recurrent ANNs can in theory process arbitrarily long strings of numbers or symbols. But training recurrent ANNs has posed much more serious practical difficulties than training feed-forward networks. ANNs are difficult to apply successfully to problems that concern manipulation of symbols and rules.

The modelling of neural networks can be identified by three phases, i.e. the training (or learning) phase, the testing phase, and the performance phase. During the training phase, the neural network is fitted to model the training data set. During the test phase, the neural network's performance is measured using the test data set in order to test if the neural network is trained well enough. During the performance phase, the actual performance of the neural network is analysed using the performance data set.

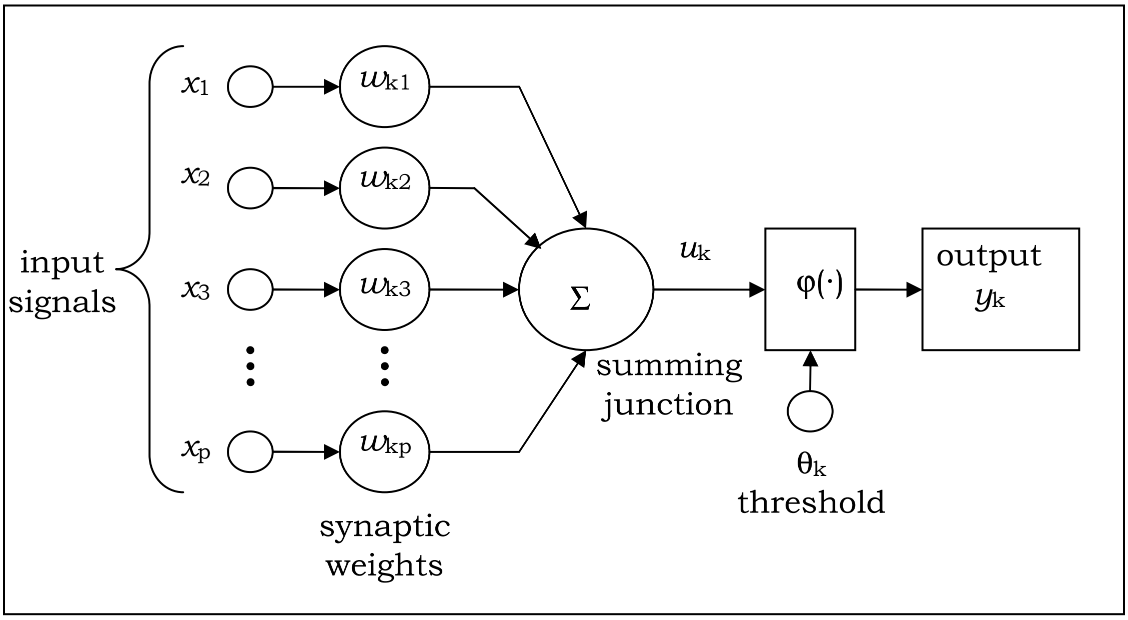

Figure 3.1: Non-linear model of an artificial neuron *k*

Artificial neurons are fundamental to the operation of any ANN and like biological neurons they can be identified by three basic elements (figure 3.1):

- *Input*: a set of signals, each of which is characterised by its synaptic weight or strength; they can be either positive (excitatory) or negative (inhibitory);
- *Adding*: all incoming signals are added at the summing junction; this is a linear combiner;
- *Output*: obtained through squashing the added input signals after subtraction of the threshold in the activation function.

In mathematical terms, a neuron *k* can be described by the following equations:

$$y_k = \varphi(u_k - \theta_k) \quad with \quad u_k = \sum_{j=1}^{p} w_{kj} \cdot x_j \tag{3.9}$$

where x_1, x_2, ..., x_p are the input signals, w_{k1}, w_{k2}, ..., w_{kp} are the synaptic weights of neuron *k*, u_k is the linear combiner output, θ_k is the threshold that can be looked upon as an external parameter, $\varphi(\cdot)$ is the activation function and y_k is the output signal of the neuron. Activation functions that are often used are the sigmoid functions such as the hyperbolic tangent function – see figure 3.2 – that can be mathematically noted as:

$$y = \tanh\left(\frac{x}{2}\right) = \frac{1 - e^{(-x)}}{1 + e^{(-x)}} \tag{3.10}$$

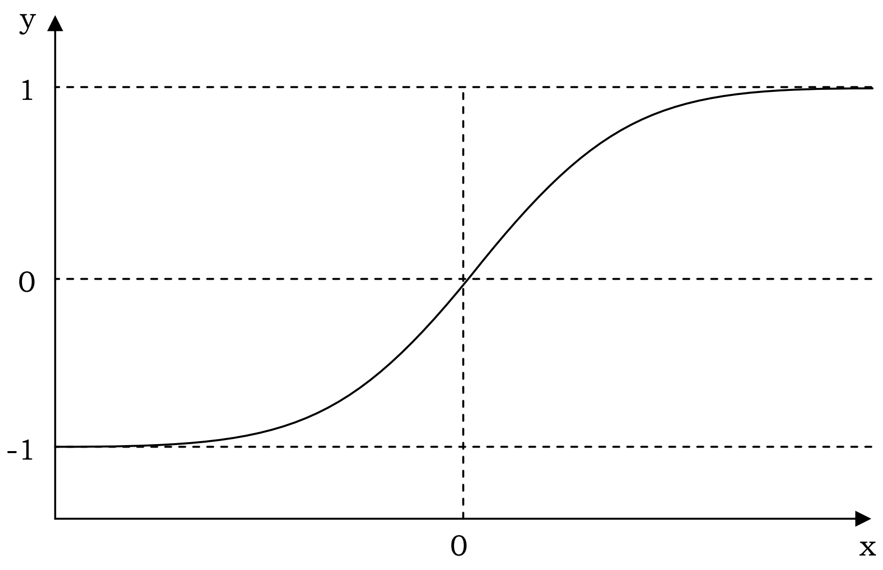

Figure 3.2: Hyperbolic tangent function

There are many kinds of ANNs by now: nobody knows exactly how many. New ones (or at least variations of old ones) are invented every week. Below is an (incomplete) overview of the collection of the most well known categories of methods.

The two main kinds of learning algorithms are supervised and unsupervised:

- In supervised learning, the correct results (target values, desired outputs) are known and are given to the ANN during training so that the ANN can adjust its weights to try match its outputs to the target values. After training, the ANN is tested by giving it only input values, not target values, and seeing how close it comes to outputting the correct target values;
- In unsupervised learning, the ANN is not provided with the correct results during training. Unsupervised ANNs usually perform some kind of data compression, such as dimensionality reduction or clustering.

The distinction between supervised and unsupervised methods is not always clear-cut. An unsupervised method can learn a summary of a probability distribution, then that summarised distribution can be used to make predictions. Furthermore, supervised methods come in two sub-varieties: auto-associative and hetero-associative. In auto-associative learning, the target values are the same as the inputs, whereas in hetero-associative learning, the targets are generally different from the inputs. Many unsupervised methods are equivalent to auto-associative supervised methods.

Two major kinds of network topology are feed-forward and feedback:

- In a feed-forward ANN, the connections between units do not form cycles. Feed-forward ANNs usually produce a response to an input quickly. Most feed-forward ANNs can be trained using a wide variety of efficient conventional numerical methods;
- In a feedback or recurrent ANN, there are cycles in the connections. In some feedback ANNs, each time an input is presented, the ANN must iterate for a potentially long time before it produces a response. Feedback ANNs are usually more difficult to train than feed-forward ANNs.

Some kinds of ANNs (such as those with winner-take-all units) can be implemented as either feed-forward or feedback networks.

ANNs also differ in the kinds of data they accept. Two major kinds of data are categorical and quantitative:

- Categorical variables take only a finite (technically, countable) number of possible values, and there are usually several or more cases falling into each category. Categorical variables may have symbolic values (e.g., “male” and “female”, or “red”, “yellow” and “green”) that must be encoded into numbers before being given to the network. Both supervised learning with categorical target values and unsupervised learning with categorical outputs are called “classification”;

- Quantitative variables are numerical measurements of some attribute, such as length in metres. The measurements must be made in such a way that at least some arithmetic relations among the measurements reflect analogous relations among the attributes of the objects that are measured. Supervised learning with quantitative target values is called “regression”.

Some variables can be treated as either categorical or quantitative, such as number of children or any binary variable. Most regression algorithms can also be used for supervised classification by encoding categorical target values as 0/1 binary variables and using those binary variables as target values for the regression algorithm. The outputs of the network are posterior probabilities when any of the most common training methods are used.

Traffic Engineering viewpoint of using the ANN methods

Artificial Neural Network models are non-linear statistical data models that are used to model complex relationships between input data and (desired) output data, also known as target data.

The supervised models are calibrated by mapping vector data in a non-linear manner onto target data, i.e. by mapping traffic patterns made up of data acquired by sensors onto the congestion prediction indicator (see chapter 7). Therefore, the models act as function approximators.

Unsupervised models try to find statistical classification within the input data and therefore act as classifiers.

All ANN models are non-deterministic models.

3.5.1 Multi Layer Feed-forward neural networks

Multi Layer Feed-forward (MLF) neural networks (McClelland and Rumelhart, 1986; Haykin, 1994; Bishop, 1995) generally exist of three or more layers; one layer of input neurons, one or more layers of hidden neurons and a layer of output neurons whereas the subsequent layers are usually fully connected (figure 3.3).

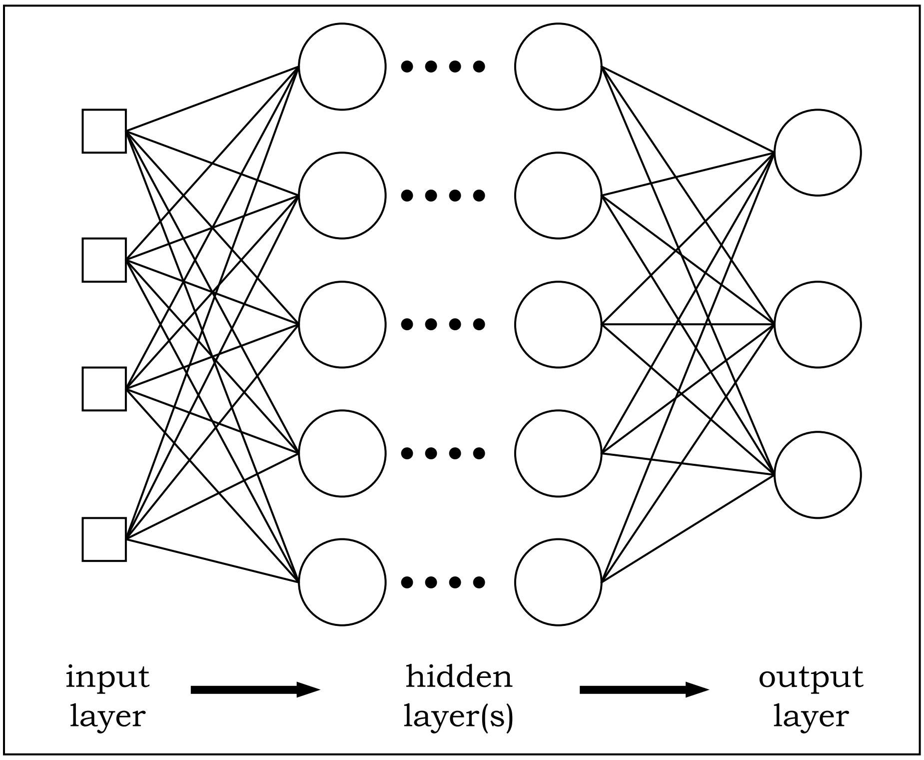

Figure 3.3: MLF neural network architecture

MLF neural networks are supervised learning networks meaning that during the training phase all inputs are mapped on desired outputs (targets). The error, i.e. the difference between the actual and the desired output, is a criterion that is used to adjust the weights of the neurons iteratively so that the total error of all input-output pairs is minimised. The algorithm responsible for this method is called the learning rule and the most commonly used one is the back-propagation algorithm. The instantaneous sum of the network error signal generated at iteration *n* is defined as the sum of all squared output layer neuron errors:

$$E(n) = \frac{1}{2}\sum_{k \in C} e_k(n)^2 \quad with \quad e_k(n) = d_k(n) - y_k(n) \tag{3.11}$$

where *e* defines the error signal of neuron *k* with *d* being the target signal and *y* defined by (3.9).

The gradient to minimise *E* with respect to the free parameters of the network (the weights) is given by:

$$\frac{\partial E}{\partial w_{kj}} = \frac{\partial E}{\partial e_k} \cdot \frac{\partial e_k}{\partial y_k} \cdot \frac{\partial y_k}{\partial u_k} \cdot \frac{\partial u_k}{\partial w_{kj}} = e_k \cdot -1 \cdot \varphi'(u_k) \cdot x_j \tag{3.12}$$

The delta rule is defined by this gradient multiplied by the rate of learning η:

$$\Delta w_{kj}(n) = \eta \cdot \delta_k(n) \cdot x_j(n) \quad with \quad \delta_k = -e_k \cdot \varphi'(u_k) \tag{3.13}$$

The back-propagation algorithm uses the delta rule to adjust the weights in the network, however, the above-described change in weights holds only for neurons belonging to the output layer. Weights belonging to the hidden layer(s) are adjusted backwards according to:

$$\Delta w_{kj}(n) = \eta \cdot \delta_j(n) \cdot x_j(n) \quad with \quad \delta_j = \varphi'(u_k) \cdot \sum_k \delta_k \cdot w_{kj} \tag{3.14}$$

MLF neural networks are the most widely and diversely used neural networks.

Traffic Engineering viewpoint of using the MLF ANN method

MLF ANNs are able, with just one hidden layer of neurons, to approximate every continuous function that maps intervals of real numbers to some output interval of real numbers if sigmoid transfer functions are used. So, if a continuous function exists that describes congestion prediction depending on traffic characteristics gathered by the sensors, ANN MLF models should be able to capture it. In practice, a possible problem is that the model overfits the training data and fails to capture the statistical properties of the training data (then the MLF ANN also tries to model the noise that is present in input data). Another danger is that MLF ANNs get stuck in a local minimum of the error function.

3.5.2 Radial Basis Function neural networks

Radial Basis Function (RBF) neural networks (Powell, 1988) are supervised neural networks that seem similar to MLF neural networks. The difference, however, can be found in the construction of the network. The input layer is made up of neurons with a linear transfer function. The second layer (the hidden layer), which has to be of a high enough dimension, has a different purpose than that of the MLF neural networks; this can be seen in that the transfer function is not a sigmoid (hyperbolic tangent) function but e.g. a Gaussian function.

The Gaussian function (see figure 3.4) can be mathematically noted as:

$$y = e^{\left(-x^2\right)} \tag{3.15}$$

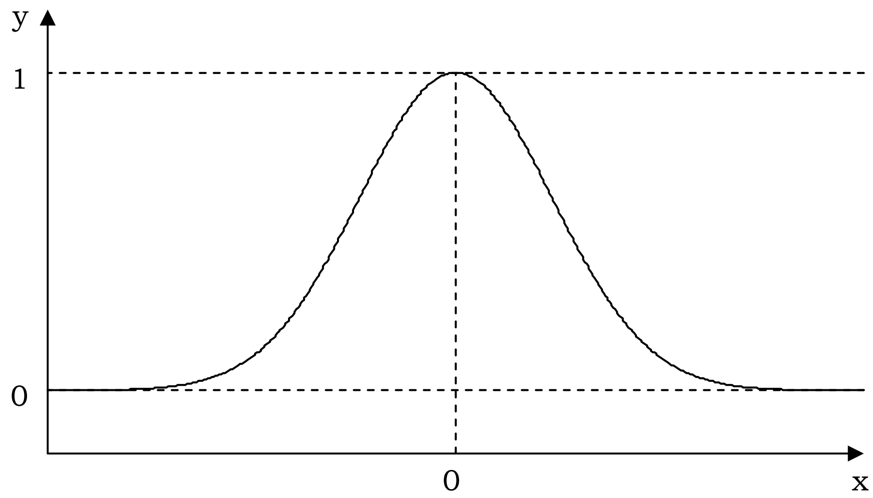

Figure 3.4: Gaussian function

This kind of activation function of the hidden layer neurons results in the isoactivation contours for RBF neural networks being concentric hyperspheres. A variety of activation functions can be used with the radial combination function, but the [exp] activation function, yielding a Gaussian surface, is the most useful. RBF neural networks typically have only one hidden layer.

Another difference between Gaussian RBF neural networks and MLF neural networks is the way in which hidden units combine values coming from preceding layers in the network: RBF neural networks use Euclidean distance, while MLF neural networks use inner products. This has consequences for the generalisation ability of the networks, especially when the number of inputs is large. MLF architectures are good at ignoring irrelevant inputs. MLF neural networks can also select linear subspaces of reduced dimensionality. Since the first hidden layer forms linear combinations of the inputs, it confines the networks attention to the linear subspace spanned by the weight vectors. Hence, adding irrelevant inputs to the training data does not increase the number of hidden units required, although it increases the amount of training data required. RBF architectures are not good at ignoring irrelevant inputs. The number of hidden units required grows exponentially with the number of inputs, regardless of how many inputs are relevant. This exponential growth is related to the fact that RBF neural networks have local receptive fields, meaning that changing the hidden-to-output weights of a given unit will affect the output of the network only in a neighbourhood of the centre of the hidden unit, where the size of the neighbourhood is determined by the width of the hidden unit.

The output layer is usually made up of neurons that have an identity activation function and supplies the response of the network to the activation patterns applied to the input layer. RBF neural networks are most often used to deal with approximation problems in a multidimensional space.

Traffic Engineering viewpoint of using the RBF ANN method

RBF ANNs are very suitable for interpolation in multidimensional space. This is particularly helpful since the traffic data sets posses quite a large number of input variables (see chapter 4). Additionally, RBF ANNs do not have the property that they get stuck in a local minimum in the error surface. However, they do have a disadvantage; they require a good coverage of the input space, meaning that they are very good at interpolation but poor at extrapolation. This characteristic may also result in modelling insignificant traffic statistics, while omitting some of the most significant ones.

3.5.3 Elman neural networks

Elman neural networks (Elman, 1990) are partial recurrent neural networks where information coming from neurons of the hidden layer serve as additional input in the next time step, the so-called context. Their learning rules are similar to the ANNs described before. Their architecture, however, is slightly different and is portrayed in figure 3.5.

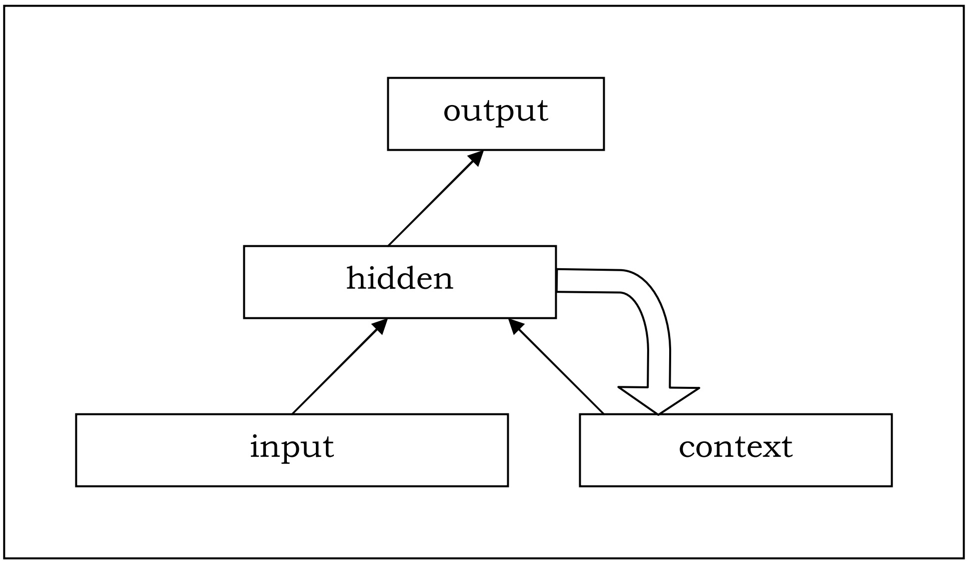

Figure 3.5: Elman neural network

The straight arrows indicate full connectivity between the neurons of the layers where information is put forward within the same time step, whereas the bend thick arrow indicates one-on-one connections where the information throughput is delayed one time step.

Elman neural networks are also known as time-space neural networks, meaning that the input of the neural network can be regarded as a space representing vector at a certain moment in time and due to the recurrent character of the network it also uses information from previous vectors which can be translated as information from the 'past' – if vectors are put in as time step vectors.

Traffic Engineering viewpoint of using the Elman ANN method

Elman ANNs are able to perform tasks such as sequence-prediction that are beyond the power of standard MLF ANNs with just one hidden layer. This is due to their quality of maintaining a copy of the previous state of the hidden layer. Since they can model non-linear mappings in combination with grasping time dependent patterns, they should be good at modelling congestion prediction. A disadvantage of Elman ANNs is that they can behave chaotic (see basic electro-engineering).

3.5.4 Self-Organising Map neural networks

SOM neural networks (Kohonen, 1995) are unsupervised neural network systems that were inspired by the way in which various human sensory impressions are neurologically mapped into the brain such that spatial or other relations among stimuli correspond to spatial relations among the neurons. SOM neural networks intend to optimise their free parameters according to statistical regularities of the input (training) data and map these input vectors onto a usually two-dimensional, but sometimes one-dimensional or (rarely) three- or more-dimensional grid. This two-dimensional (usually either rectangular or hexagonal) lattice structure (figure 3.6) exists in a space that is separate from the input space; any number of inputs may be used as long as the number of inputs is greater than the dimensionality of the grid space. A SOM neural network tries to find clusters such that any two clusters that are close to each other in the grid space have codebook vectors close to each other in the input space. But the converse does not hold: codebook vectors that are close to each other in the input space do not necessarily correspond to clusters that are close to each other in the grid. Another way to look at this is that a SOM tries to embed the grid in the input space so that every training case is close to some codebook vector, but the grid is bent or stretched as little as possible. Yet another way to look at it is that a SOM is a (discretely) smooth mapping between regions in the input space and points in the grid space.

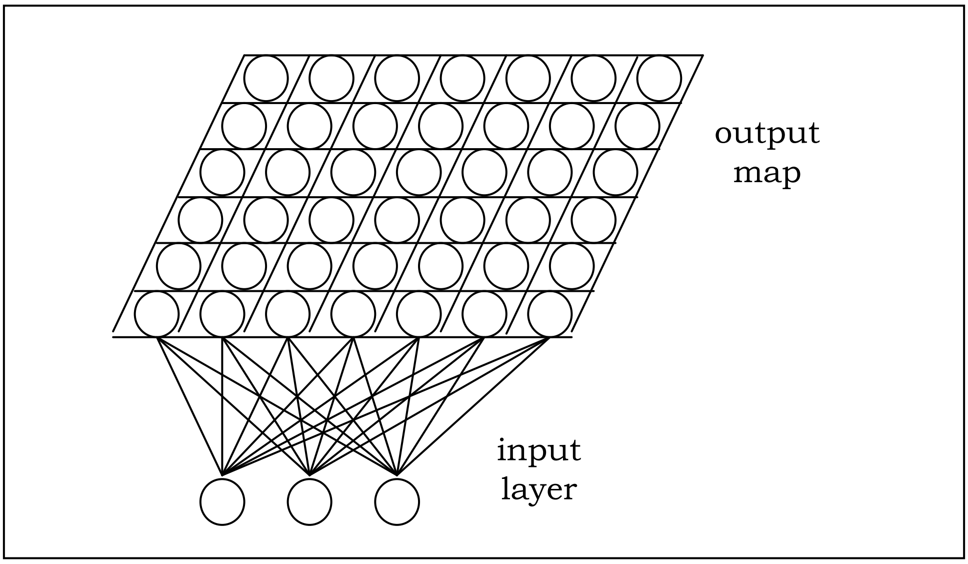

Figure 3.6: Two-dimensional Kohonen map

SOM neural networks are competitive networks that provide a ‘topological’ mapping from the input space to the clusters. When input are presented to the network all neurons of the lattice structure are stimulated and the neuron with the biggest activation is declared ‘winner’. The weights between the input neurons and the winning neuron are strengthened, as well as, but not as strong as, the weights connecting the input neurons to the neighbouring neurons. After the network is tuned and new input data are offered the data are mapped onto the lattice area that has the most statistical similarity to the training data. Self-Organising Maps are also known as Kohonen maps and are most often used to deal with classification problems.

Traffic Engineering viewpoint of using the SOM ANN method

SOM ANNs are especially well suited for representing high-dimensional data in low-dimensional topologies. Every part of the output lattice is associated with a statistical property of the input data set. When this is transposed to congestion prediction, there is yet no certainty as to which statistical properties of the acquired input variables are most significant to congestion prediction, especially when the prediction horizon changes and geographical properties alter. Therefore this method might be able to produce surprising results, although it has until now never solely been used as a model in this context.

3.6 Fuzzy Logic

The concept of Fuzzy Logic (FL) was conceived by Zadeh (1965), and presented as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership. It deals with reasoning that is approximate rather than precise. This approach to set theory was not applied to control systems until the 70's due to insufficient small computer capability prior to that time. FL is based on the analogy of the reasoning of people; they do not require precise, numerical information input, and yet they are capable of highly adaptive control. If feedback controllers could be programmed to accept noisy, imprecise input, they would be much more effective and perhaps easier to implement.

FL is a heuristic, problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. FL's approach to control problems mimics how a person would make decisions, only much faster.

FL incorporates a simple, rule-based IF X AND Y THEN Z approach to a control problem rather than attempting to model a system mathematically. The FL model is empirically based, relying on an operator's experience rather than their technical understanding of the system. For example, instead of dealing with temperature control in terms such as "Temp = 273.15 K" (freezing temperature of water), "Temp < 78 F" (typical afternoon temperature forecast in October for Orange County, CA), or "210 C < Temp < 220 C" (baking instructions for a pizza), terms like "IF (process is too cool) AND (process is getting colder) THEN (add heat to the process)" or "IF (process is too hot) AND (process is heating rapidly) THEN (cool the process quickly)" are used. These terms are imprecise and yet very descriptive of what must actually happen. Consider what you do in the shower if the temperature is too cold: you will make the water comfortable very quickly with little trouble. FL is capable of mimicking this type of behaviour but at very high speed.

Fuzzy Set Theory, as it is often also called, can also be regarded as an extension of ordinary set theory, i.e. elements are not just 'member' or 'no member' of a certain set but can have a degree of membership (between 0 and 1). A fuzzy system consists of fuzzification, inference and defuzzification processes.

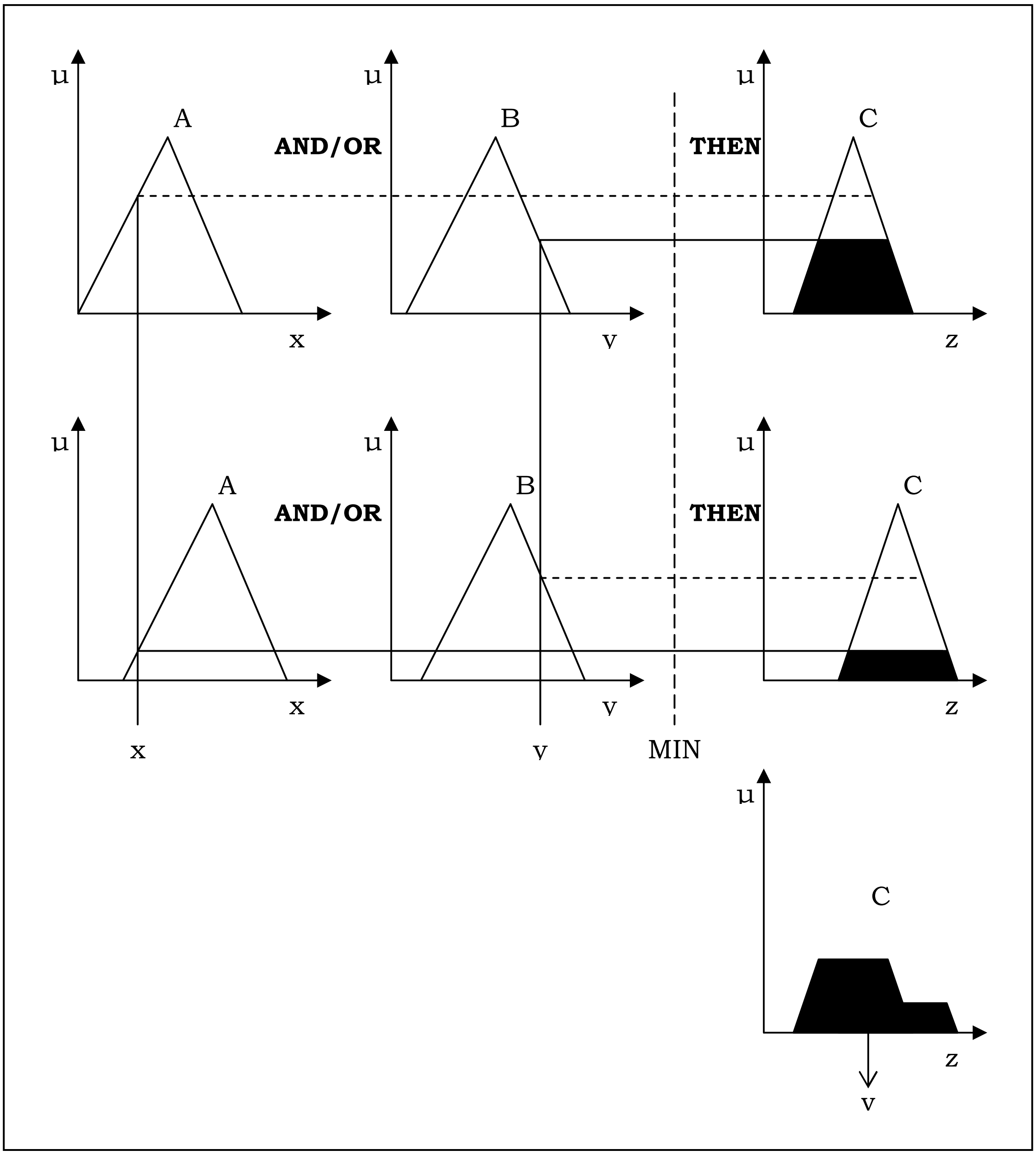

Figure 3.7: Fuzzy inference scheme

The fuzzification process (figure 3.7) is designed to assign degrees of membership (μ) to crisp input values (x_0, y_0) by means of lookup in one or several membership functions (A_1, A_2, B_1, B_2) These membership functions correspond with linguistic terms that apply to input variables and should be partially overlapping and sufficiently wide to allow for noise in measurements. Not only input but also output variables are fuzzified (C_1, C_2).

The inference method uses a fuzzy rule base (or knowledge base as it is sometimes called) that is made up of logical operations and is based on expert opinions, operator experience, and/or system knowledge. The rules are given according to the following format:

IF <*premise 1*> AND/OR <*premise 2*> AND/OR <*premise 3*> … THEN <*consequence*>

Because a fuzzy rule based system consists of a set of fuzzy rules with partially overlapping conditions, a particular input to the system often triggers multiple fuzzy rules. Therefore a method is needed to combine the inference results of these rules. This is accomplished typically by mapping all fuzzy conclusions onto one variable (z).

Finally, the obtained fuzzy output variables need to be translated into a crisp output value. This process is called defuzzification and is established by using a method, e.g. the centre of gravity approach, which allocates a crisp value to the final outcome (v).

Traffic Engineering viewpoint of using the FL method

FL is suited for dealing with complex optimisation problems with many constraints and objectives, with unclear input information and vague decision criteria. This category contains many problems in the fields of traffic and transportation (Teodorović, 1999). FL is also used extensively as a control method in various applications, e.g. for determining green times for traffic lights (Niittymäki, 2001) or for optimizing ramp metering algorithms (Taale *et al.*, 1991). Since control and prediction share some properties, the FL method should be considered a good candidate for congestion prediction. Additionally, the relation between traffic indicators, as they are measured through sensors, and congestion prediction can be characterised as unclear and vague; this is another reason to promote this method.

3.6.1 Adaptive-Network-based Fuzzy Inference Systems

The Adaptive-Network-based Fuzzy Inference Systems (ANFIS) is a neuro-fuzzy variant of FL. The concept of neuro-fuzzy models has emerged in recent years as researchers have tried to combine the transparent, linguistic representation of a fuzzy system with the learning ability of artificial neural networks and dates back to Kosko (1992). ANFIS uses a hybrid-learning algorithm to identify the parameters of the fuzzy inference schemes. It applies a combination of the least-squares method and the back-propagation gradient descent method for training FIS membership function parameters to emulate a given training data set (Jang, 1993).

ANFIS applies two techniques in updating parameters. For premise parameters that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equation, ANFIS uses the least-squares method to identify them. This approach is thus called the hybrid learning method since it combines gradient descent and the least-squares method.

ANFIS can also be invoked using an optional argument for model validation. The type of model validation that takes place with this option is a checking for model over-fitting, and the argument is a data set called the checking data set.

Traffic Engineering viewpoint of using the FL ANFIS method

Embedding an FIS in a general structure of an ANN has the benefit of using available ANN training methods to find the parameters of a fuzzy system. In short: FL ANFIS incorporates the ability to model unclear input information and vague decision criteria and uses a powerful training method to find the optimal model parameters as is the case in congestion prediction. A disadvantage is that this method uses quite a bit of computational time which increases dramatically with increasing model parameters.

3.7 Synthesis

This paragraph provides an overview of the methods that were described before; how do they relate to each other with regard to input data, (non-)linearity, (non-)deterministic nature, and (un)supervised calibration/learning phase. To demonstrate these relations, a table has been set up where all methods score on the parameters mentioned (table 3.1).

The table is made up of methods and their most descriptive parameters. Obviously, there are more parameters that make more rigorous distinctions between methods such as transfer function (to come to a distinction between MLF-ANNs and RBF-ANNs) but it is beyond the scope of this section to describe the methods in every detail. To become more acquainted with the methods, the interested reader is referred to many excellent textbooks, some of which were already mentioned in this section.

Table 3.1: Overview of the described methods

Parameter Method	*maximum # of input variables*	*linear vs. non-linear*	*deterministic vs. non-deterministic*	*supervised vs. unsupervised*
Naïve	1	Linear	deterministic	unsupervised
MLR	∞	Linear	deterministic	supervised
ARMA(X)	1 (∞)	Linear	deterministic	supervised
MLF-ANN	∞	non-linear	non-deterministic	supervised
RBF-ANN	∞	non-linear	non-deterministic	supervised
Elman-ANN	∞	non-linear	non-deterministic	supervised
SOM-ANN	∞	non-linear	non-deterministic	unsupervised
ANFIS	4	non-linear	deterministic	supervised

CHAPTER 4

Data acquisition

"We have to remember that what we observe is not nature in itself but nature exposed to our method of questioning."

Werner Heisenberg

4.1 Introduction

The section reports on the locations that were identified for data acquisition, and describes the collected data sets qualitatively and quantitatively. This search for locations resulted in two cloverleaf junctions: 'Beekbergen', near the city of Apeldoorn (junction of motorway A1 with motorway A50) and 'Hoevelaken', in close proximity to the city of Amersfoort (junction of motorway A1 with motorway A28).

4.2 Location selection

Our initial study area was the whole of The Netherlands. At least two locations with bottlenecks were needed to check location transferability of the method's performance results (demand 1). These locations have to suffer from congestion during both the morning and the evening peak hours (demand 2). Locations equipped with detectors for data collection were also needed (demand 3). Since the majority of the Dutch motorway system is equipped with dual induction loop detectors this demand is easily met. However, there are several data acquisition systems active and in order to be able to compare results, the locations should be fitted with the same data acquisition system (demand 4). Due to the amount of data that is gathered with the MoniCa (Monitoring Casco) system this system was chosen (demand 5).

After receiving information on all locations equipped with MoniCa detectors additional demands were considered. Locations that were isolated with respect to other locations with bottlenecks were preferable to exclude congestion interaction (demand 6). It would also be of added value if these locations did not suffer from severe day-to-day congestion; this would make the prediction task more difficult because of extra unpredictability (demand 7). If both locations had a comparable road infrastructure layout (e.g. same number of lanes) this would also benefit their comparability (demand 8).

The above-described demands led to the selection of the following two locations: the 'Beekbergen' cloverleaf junction and the 'Hoevelaken' cloverleaf junction. These two junctions are within 50 kilometres of each other, which had another additional benefit: the weather conditions would be similar for both junctions for most of the time so its influence would be minimal if comparisons of the method's performances based on location were made (demand 9).

Data acquisition took place during the year 2001. Whenever transportation studies are performed that will include comparisons based on real data they are usually done with data collected during spring or fall to exclude particular circumstances (snow, summer vacation). In the Netherlands spring is the more obvious choice because of the more stable weather patterns (demand 10). After checking the spring months to see which month had the highest percentage of properly functioning detectors (demand 11) the month of May of the year 2001 was selected (see appendix D for availability percentages of the Beekbergen and Hoevelaken detectors).

4.3 Dual induction loop detectors

Inductive Loop Detectors (ILDs) are the most common technology used on freeways and arterial roadways to collect real-time data on vehicle presence, traffic speed, and vehicle length. Loop data is used to actuate traffic control devices and to detect congestion and queuing as well as crashes and breakdowns on the roadway (Lin and Daganzo, 1997; Jin *et al.*, 2002). Loops represent a mature technology and there are thousands already deployed across The Netherlands.

An inductive loop detector (figure 4.1) consists of a loop usually several meters wide, made of twisted, insulated wire embedded in the roadway. Loops take a variety of shapes (square, rectangle, octagon, diamond, circle). Each shape has somewhat different electromagnetic properties. A lead-in wire connects the loop with a roadside “pull box”, which simply houses the splice between this lead-in wire and the cable to the electronic controller unit. Lead-in wires are insulated to protect them from electronic disturbances produced by other nearby electrical sources, including other loops. The electronic controller unit, which amplifies and processes the signals from the loop, is usually housed in a rugged cabinet in a safe accessible location away from the roadway. This unit also provides the power that activates the loops as well as software that allow “tuning” and calibration of loop electronics so they will accurately sense the presence of vehicles on the roadway above. One controller operates about forty loops. Controllers may transmit their data directly to field equipment such as traffic signals or send their data back to a centralized Traffic Management Centre (TMC) using wired or wireless technologies.

A loop is excited by an electronic signal ranging in frequency from 10 kilohertz to 200 kilohertz, which creates an electromagnetic field. When a vehicle passes over the loop or stops on top of it, the vehicle’s undercarriage acts as a conductor, reducing the inductance of the loop. The decreased inductance increases the oscillation frequency in the loop and sends a pulse through the lead-in wires and cable to the controller. In most conventional installations, the inductance or frequency change must cross some preset threshold before the controller will interpret the changes as a vehicle. Data from the loops are sent to the controller every few seconds.

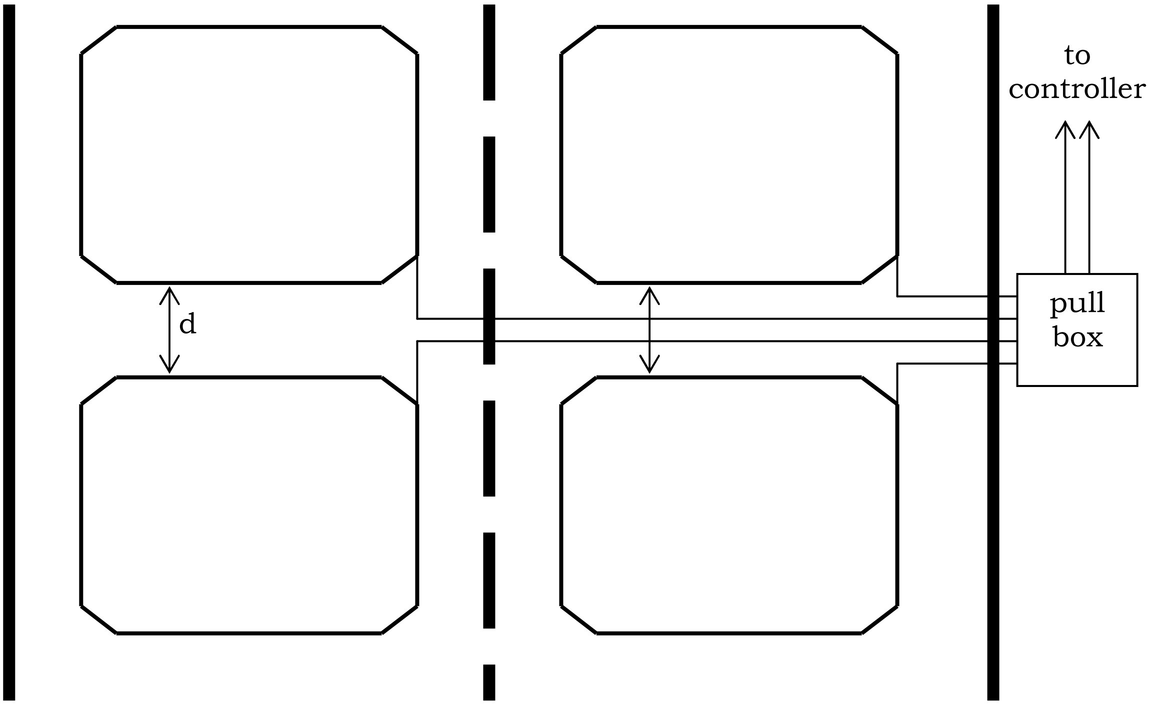

Figure 4.1: *Dual induction loop detectors.*

Various algorithms are used to manipulate basic loop data to generate information about traffic flow (counts or intensities), speeds and vehicle category (by including the known distance *d*), and occupancy. Factors such as wire size, wire length, number of turns, lead length, and insulation determine loop inductance. The ability of a loop to sense a vehicle is also dependent on the distance between the loop wire that is embedded in the roadway and the vehicle's metal undercarriage.

Loop detectors have been used for more than 25 years and are the backbone for the traffic management and data collection system. They can be placed below the surface of the roadway, although loop sensitivity decreases. Additional loop turns will emit a stronger electromagnetic field and compensate for roadway interference. The type of wire used also affects loop operation.

4.4 Location 'Beekbergen'

'Beekbergen' is a cloverleaf junction located in the mid/east-Netherlands. Figures 4.2 and 4.3 show aerial photos of the data collection site 'Beekbergen' near the cities of 'Apeldoorn' and 'Deventer', while figure 4.4 shows the overview of the data collection site. Figure 4.5 shows the cloverleaf junction in more detail.

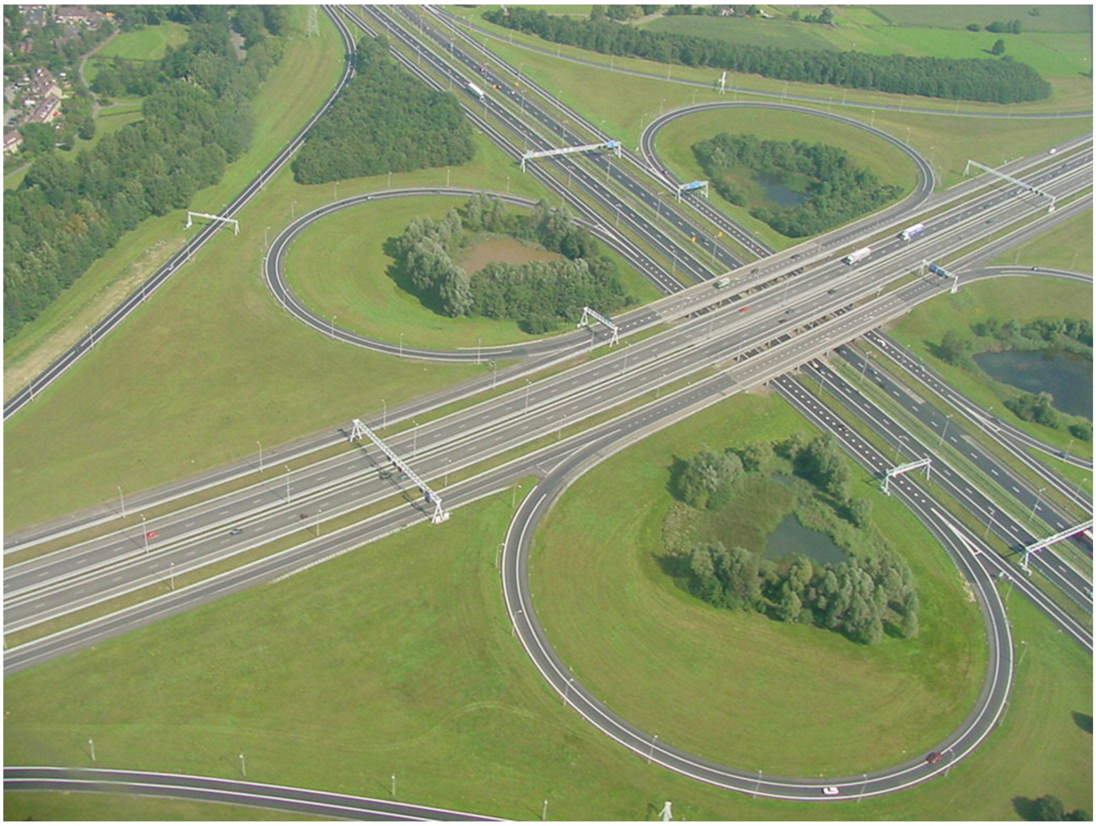

Figure 4.2: *Aerial photo of the 'Beekbergen' cloverleaf junction.*

Figure 4.3: *Aerial photo of the 'Beekbergen' cloverleaf junction – tilted angle.*

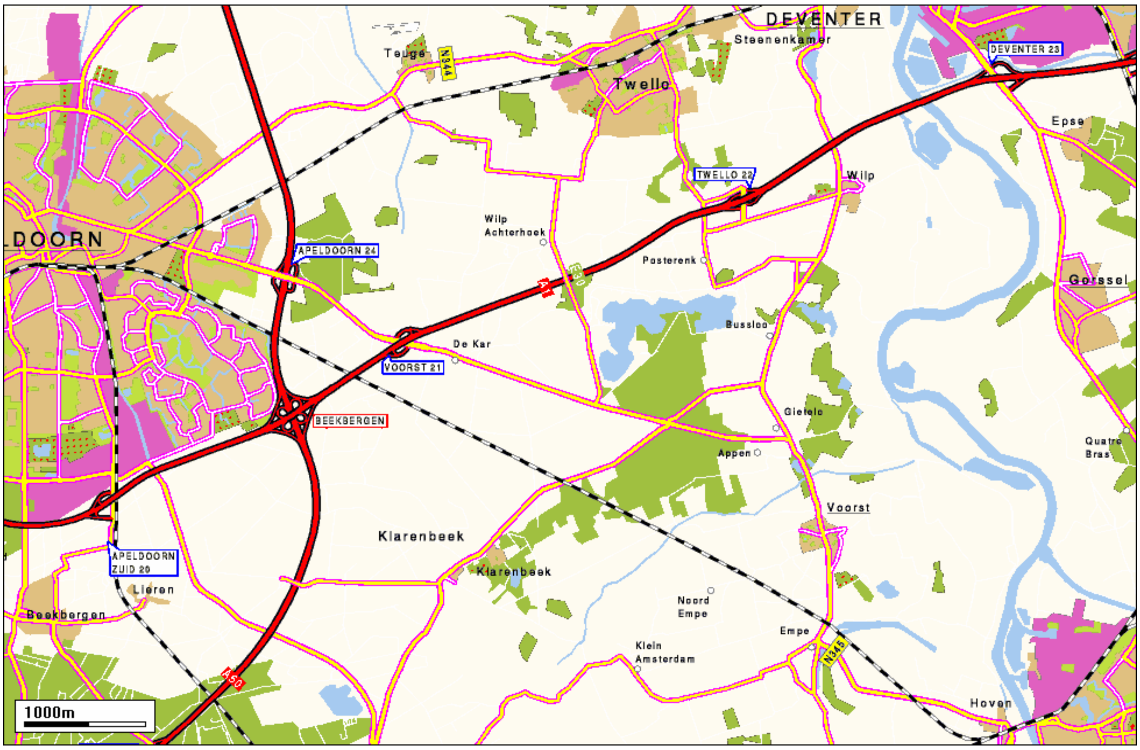

Figure 4.4: *The 'Beekbergen' cloverleaf junction.*

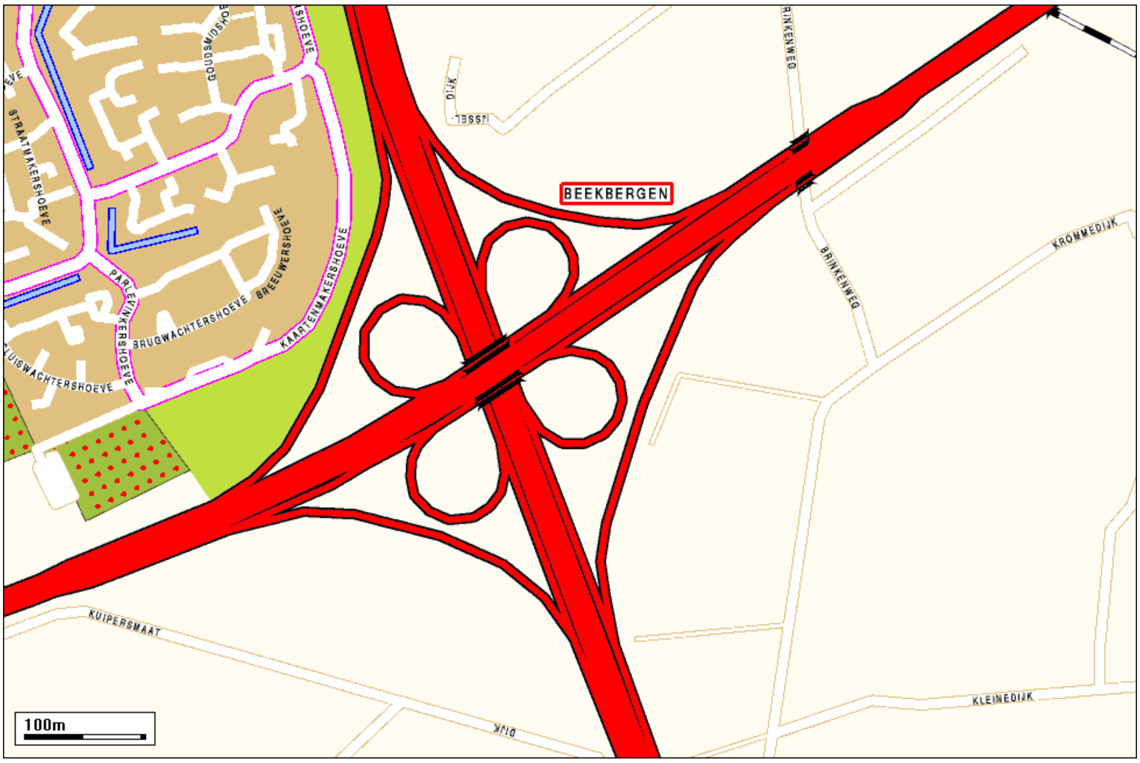

Figure 4.5: *The 'Beekbergen' cloverleaf junction – in more detail.*

Figure 4.6 shows the total site where induction loop detectors are present that were used to gather the first data set. This site uses detectors of the motorway A1 (west-east direction): from 2 kilometres west of the junction to 11 kilometres east of the junction. Detectors of the motorway A50 (south-north direction): from 3 kilometres south of the junction to 3 kilometres north of the junction. For both motorways the detectors in both directions were used as traffic data sources.

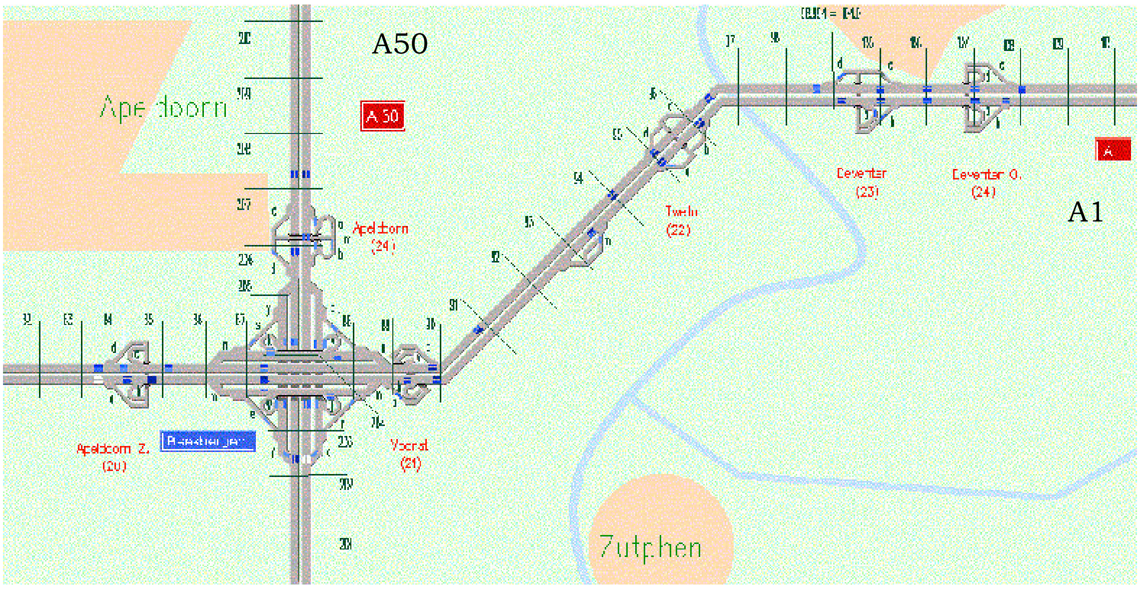

Figure 4.6: *The 'Beekbergen' study area – schematic representation used in the traffic management centre including the detector locations.*

4.5 Location 'Hoevelaken'

'Hoevelaken' is a cloverleaf junction located in the mid-Netherlands. Figure 4.7 shows an overview of the data collection site 'Hoevelaken' near the city of 'Amersfoort', and figure 4.8 shows the cloverleaf junction in more detail, while figures 4.9 and 4.10 show aerial photos of the data collection site. Figure 4.11 displays the total site where induction loop detectors are present that were used to gather the first data set. This site uses detectors of the motorway A1 (east-west direction): from 2 kilometres west of the junction to 11 kilometres east of the junction. Detectors in the motorway A28 (north-south direction): from 3 kilometres south of the junction to 3 kilometres north of the junction. For both motorways the data from detectors in both directions were used.

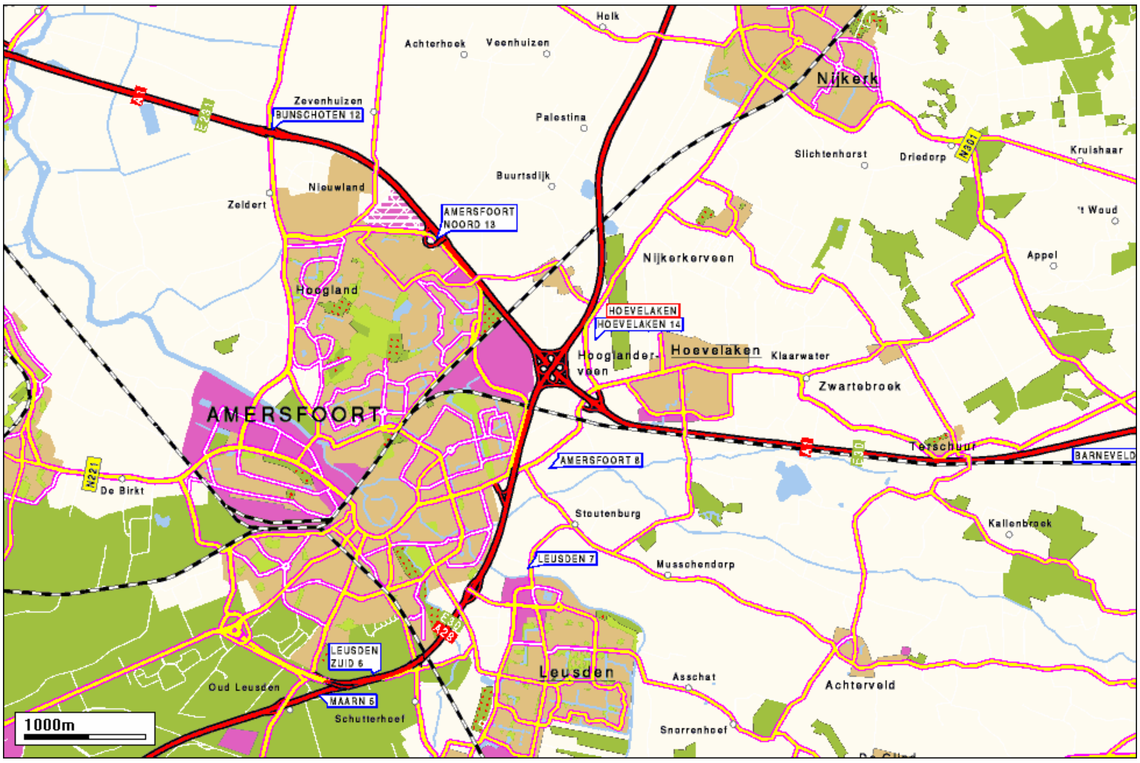

Figure 4.7: *The 'Hoevelaken' cloverleaf junction.*

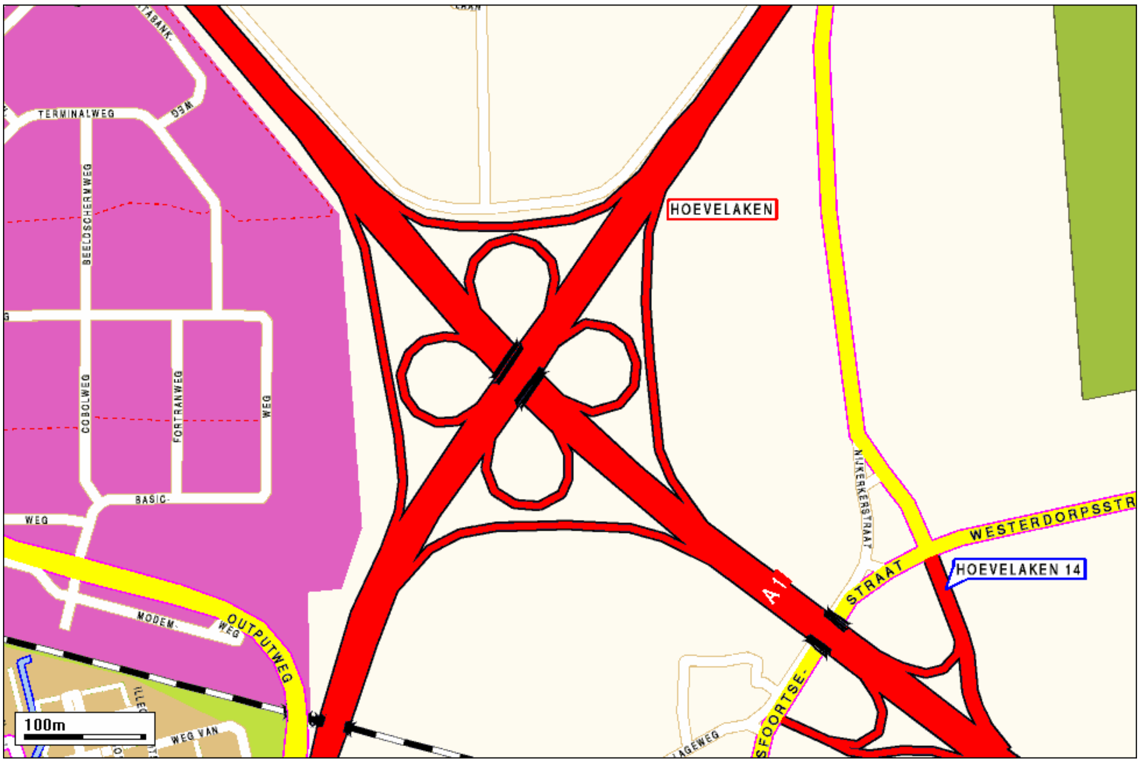

Figure 4.8: *The 'Hoevelaken' cloverleaf junction – in more detail.*

Figure 4.9: *Aerial photo of the 'Hoevelaken' cloverleaf junction.*

Figure 4.10: *Aerial photo of the 'Hoevelaken' cloverleaf junction – tilted angle.*

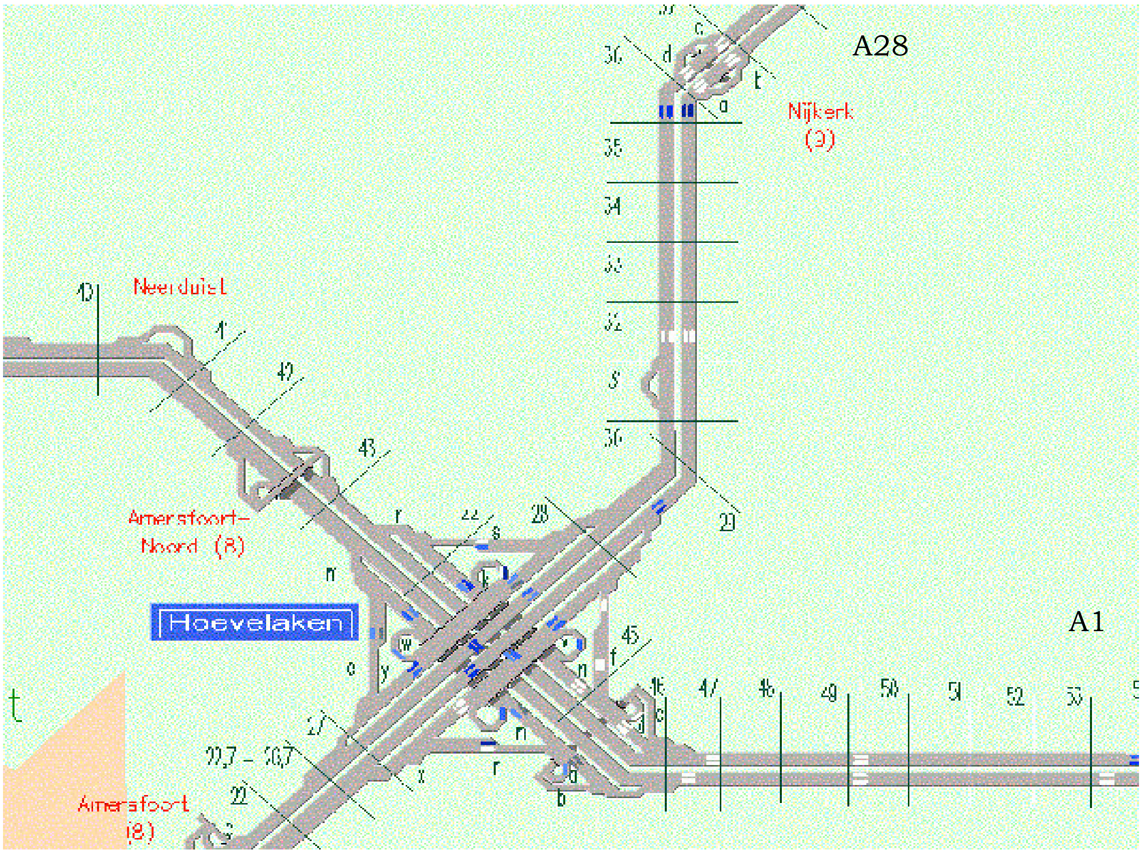

Figure 4.11: *The 'Hoevelaken' study area – schematic representation used in the traffic management centre including the detector locations.*

4.6 The data set description

MoniCa data consists of several variables: it is acquired in 1-minute time bins that hold data on:

- The detector identification number;
- The day it was acquired;
- The minute it was acquired;
- The reliability;
- The seconds it was function properly during the acquisition minute;
- The occupancy (% of time that the detector is covered by a vehicle);
- A congestion indicator (see below);
- Three categories of vehicles, i.e.:
    - Category 1: vehicle length < 5.1 metres;
    - Category 2: vehicle length > 5.1 and < 12.5 metres;
    - Category 3: vehicle length > 12.5 metres.

For each vehicle category:

- The mean speed;
- The standard deviation of the mean speed;
- The intensity (volume; number of vehicles per hour).

The congestion indicator is switched 'on' if five consecutive vehicles are detected with a speed that is less than 35 kilometres per hour and is switched 'off' if subsequently five consecutive vehicles with a speed higher than 50 kilometres pass the detector.

4.7 Initial data filtering

All unreliable data were removed and all missing data were substituted by the last known reliable data. Data from the month of May 2001 consisted of 31 days of data. The only interested days are working days so all Saturdays and Sundays were eliminated; this left 23 days of data. It was planned to end up with four sub-sets of data with each day of the working week represented in each sub-set. From each of the sub-sets of 3 days when there were 5 replicates, the replicate with the most unreliable or missing data was removed. Thus this gave 4 sub-sets containing a Monday, a Tuesday, a Wednesday, a Thursday, and a Friday. Since the morning peak hours (05:00 – 09:59 hours) and evening peak hours (15:00 – 19:59 hours) during working days were the only hours of interest, the remaining data were also omitted. Thus the sub-sets which were analysed were:

- A morning peak data set of 'Beekbergen';
- A evening peak data set of 'Beekbergen';
- A morning peak data set of 'Hoevelaken';
- A evening peak data set of 'Hoevelaken'.

Each data set now consists of four sub-sets and within each of these sub-sets every working day is represented. The sub-sets need additional pre-processing before they can be used to calibrate and assess the models; these procedures are described in chapter 6.

CHAPTER 5

Hypotheses

"There's two possible outcomes:
If the result confirms the hypothesis,
then you've made a discovery.
If the result is contrary to the hypothesis,
then you've made a discovery."

Enrico Fermi

5.1 Introduction

The research described in this thesis tries to answer the main question stated in chapter 1:

> *Which of the methods gives the best congestion predictions on motorways within the short-term horizon and under what circumstances are these predictions achieved?*

Chapter 2 mentioned a list of variables that are possibly of influence during the data set gathering procedure. One approach is to try to investigate the influence of every variable on each method's performance by changing one variable and keeping the other variables constant, but since the data were not acquired under laboratory conditions (to account for e.g. weather conditions) this is not possible. Therefore another approach that will (hopefully) benefit the transport science community has been adopted: transport related hypotheses on matters that are relevant to the method's performances on predicting short-term congestion are stated and by analysing the generated results and the model parameters these hypotheses will either be confirmed or rejected.

In this chapter the hypotheses are given; each one of them is preceded by previously described research, opinions and / or thoughts on why they are written down as they are. The next chapters describe the data pre-processing and model development, while in chapter 8 the results are analysed and chapter 9 reports on the confirmation / rejection of the hypotheses defined below and the accompanying arguments derived from the analysis results for doing so.

5.2 Hypotheses

The data sets described in chapter 4 contain several variables. It is therefore possible to define numerous hypotheses that incorporate the influence of these variables. A selection of the most interesting hypotheses follows below.

5.2.1 Hypothesis 1

How far ahead in the future does congestion prediction still make sense? The answer to this question depends on several issues. The accuracy of congestion prediction will deteriorate as the prediction horizon increases due to uncertainty (see Dougherty *et al.*, 1993;

Huisken, 2000; Huisken and Coffa, 2000; Huisken and van Maarseveen, 2000; Huisken, 2001a). The point in space where one wants to predict congestion is the detector closest to the spot where congestion usually sets in. Once this target detector has been located, the answer to the question above depends theoretically on the number of detectors upstream of the target detector and the space that this detector-equipped section spans. Vehicles entering the section will take a period of time to travel to the target detector, defined as the section travel time period. It is clear that vehicles that are outside the section, and thus outside the section travel time period, cannot be detected. Combining both issues addressed above, the following hypothesis is postulated:

Hypothesis 1:

> *Any method's accuracy will deteriorate with increasing prediction horizon. The rate of increase will alter when the prediction horizon exceeds the travel time period of the monitored section.*

5.2.2 Hypothesis 2

Another important issue that is somewhat related to the previous hypothesis is the period of time in which congestion builds up (i.e. rapid build up during a short period or slow build up during a longer period). The congestion build-up period has influence on the relative importance of information coming from the individual detectors since the change in values coming from a detector every minute will be bigger during a short period than with a longer period. Because congestion in the morning peak usually builds up faster than the evening peak this leads to the next hypothesis:

Hypothesis 2:

> *Due to the different (faster) congestion build-up in the morning peak compared to the evening peak, the significance of individual detectors will alter faster during the morning peak than during the evening peak and therefore the method's prediction of the evening peak will outperform that of the morning peak.*

In other words: the morning peak sets in more abruptly and is therefore more difficult to predict than the evening peak.

5.2.3 Hypothesis 3

More information means less uncertainty (Shannon, 1947). If methods that use spatial information would also receive temporal information, the amount of information would increase and therefore these methods should perform better than methods that lack the additional temporal information. Hence the following hypothesis:

Hypothesis 3:

Feedback information from previous time steps does significantly improve the method's performance.

Since MLF ANNs use the same information as State-Space (Elman) ANNs do, with the exception that Elman ANNs use the output from time *t-1* as input for time *t*, this hypothesis can be checked by comparing the performance results obtained by the two methods.

5.2.4 Hypothesis 4

Congestion is a highly non-linear phenomenon (U.S.DoT, 1997). Methods that are able to model non-linearity should be better at modelling a non-linear phenomenon like congestion prediction than methods that are limited to model linear phenomena only, given the same information. This leads to the next hypothesis:

Hypothesis 4:

Methods that are able to model non-linearity will outperform methods that use linear modelling when it comes to a non-linear phenomenon like congestion prediction.

MLF ANNs use the same information as MLR does, the difference being that MLF ANNs use non-linear processing and thus are able to model non-linearity, while MLR uses linear processing. This hypothesis can be either rejected or confirmed by comparing the performance results of the two methods.

5.2.5 Hypothesis 5

Methods that use information on events to come (= vehicles upstream) should be better for predicting congestion than methods that use information from the past. Therefore hypothesis 5 is postulated:

Hypothesis 5:

Upstream spatial induction loop information provides more useful information for predictions than historical temporal induction loop information from the bottleneck.

This hypothesis can be checked by comparing the ARMA time series analysis performance results with those of MLR. Obviously, when both hypothesis 4 and 5 are confirmed this then leads to hypothesis 5a:

Hypothesis 5a:

MLF ANNs will outperform ARMA time series.

5.2.6 Hypothesis 6

Congestion is usually divided into recurrent and non-recurrent congestion. Recurrent congestion sets in on a daily (working day) basis and manifests itself at approximately the same time of day. Non-recurrent congestion demonstrates itself irregularly and is more difficult to predict. Which methods are better at predicting recurrent congestion, and will the best performing methods also give the best results for predicting non-recurrent congestion? This question leads to hypothesis 6:

Hypothesis 6:

The methods that perform best at predicting recurrent congestion are the same as those that give the best performances in predicting non-recurrent congestion.

To either confirm or reject this hypothesis data on recurrent and non-recurrent congestion traffic conditions has to be acquired and assessed.

5.2.7 Hypothesis 7

The input data vector is made up of input variables. Those variables are fed with detector loop data. Each vector index corresponds with a certain variable from a certain detector. If traffic patterns are fed to the model, the parameters / architecture of the model should be different for different prediction horizons (otherwise the model should generate the same results for different prediction horizons). This logically results in hypothesis 7.

Hypothesis 7:

The parameters / weights of a model will alter with changing prediction horizons.

The input weights of the model can be checked easily to either confirm or reject this hypothesis.

5.2.8 Hypothesis 8

Heavy traffic influences traffic flow in that it has a positive impact on the amount of chaos in the traffic flow due to the lower mean speed of trucks. In the absence of trucks the traffic flow is more homogeneous and according to e.g. Smulders (1990) this leads to higher intensities before the traffic flow breaks down into congestion.

Hypothesis 8:

Due to the presence of heavy traffic, congestion will occur while traffic intensities are substantially below traffic congestion intensities in the absence of heavy traffic. Effectively, capacity will deteriorate.

This hypothesis has no immediate significance for the choice of a prediction method. However, it does have influence on pre-processing. If the hypothesis is confirmed, it leads to the conclusion that information on heavy traffic has added value and should therefore improve prediction results when it is used as additional input data.

CHAPTER 6

Pre-processing

"Everything should be made as simple as possible, but not one bit simpler."

Albert Einstein

6.1 Introduction

The section reports on the pre-processing of the data that was collected as described in chapter 4. This resulted in a data set that incorporates the data acquired on two locations:

- Around cloverleaf junction Beekbergen;
- Around cloverleaf junction Hoevelaken.

This data set cannot be used in its present configuration for input or calibration purposes with respect to the congestion prediction models. First the specifications that are needed in order to come to suitable data sets for the model calibration process as well as to serve as input data sets to assess the models will be described. After specification information on the steps that have to be taken to transform the data sets so that they will fulfil the specifications will be given.

6.2 Data set specifications

The specifications of the data set are related to the research question. The acquired data have to be prepared in such a fashion that the research question and hypotheses stated in chapter 5 can be answered. The specifications that apply to the original data set are now described.

The models based on the location were the data was acquired will be assessed. This means that the data set has to be divided in a Beekbergen data set and a Hoevelaken data set.

Since predicting congestion is the key interest, it makes sense to remove days that are likely to not include congestion. Therefore the weekend days Saturday and Sunday will be left out.

As was mentioned before in chapter 3, all prediction methods that will be used are data driven. This implies the need for data to calibrate and validate the models. This can cause problems because decisions on which part of the data set will be used to calibrate the models and which part will be used to validate the models have to be taken. A proper solution to this problem is to use cross-validation, i.e. the division of the data set in sub-sets and to use a major part to calibrate the model. Then the remaining part is used to validate the model. After this exercise the same routine will be followed but with another sub-set as validation set and this procedure will be repeated until all sub-sets are used as validation set. The average of all sub-set validations is used for establishing the performance of the models.

Equally sized sub-sets are needed to perform cross-validation. Since the data was acquired during the month of May of 2001 the data set can easily be divided in four one-week sub-sets so each day of the week is represented in each sub-set.

However, the month of May of 2001 has five Tuesdays, Wednesdays, and Thursdays. One of each of these days has to be removed in order to get equally sized sub-sets.

Reliability and missing data is also an issue. Not all dual loop detectors report with 100% reliability all the time. Therefore unreliable data that can be identified by the reliability indicator and missing data have to be removed and/or substituted with the last known reliable data.

In order to build data sets that contain data that are relevant, the bottlenecks need to be identified, i.e. the dual loop detector that usually will be the first one to detect congestion. The congestion indicator data reported by this detector will then be used as target data. The identification of this detector is also needed to select relevant detectors in the sense that they are located either upstream or downstream in the vicinity of the bottleneck detector. In that way data coming from detectors that are located on a lane on which traffic is driving in the opposite direction can be omitted.

Also, during the day there are two periods that will incorporate congestion, i.e. during the morning peak and during the evening peak. The remaining periods will have to go.

Finally, the data have to be normalised so that every model can receive and process the same input data during the evaluation process.

In short: the acquired data set has to be transformed into four times four normalised working-week based data subsets (four weeks for each location and peak period) that are reliable and are ordered in such a fashion that the order of columns (‘attributes’) are depending on spatial distance from the bottleneck location and rows (‘entries’) are depending on the acquisition time of day.

6.3 Pre-processing steps

Now that the data specifications are described they can be translated into pre-processing steps to go from received zipped files to the above-specified files. Each day holds 1440 data files (one file for each minute) that contain information acquired through induction loops; 1-minute aggregated information on traffic flow, mean velocity and its standard deviation, and occupancy.

The pre-processing steps are:

- *Unzip the files*; since all files were received as zipped files, all files have to be unzipped;

- *Put all files together*; all unzipped files are copied on a day-to-day basis into one file. The result is one file for every day of the month of May 2001. A section of May 1st (at 08:30 a.m.) looks like this:

[RSW]												
[SIV]	988698600	**01-05-01**	**8:30**	**j**	**60**	**60**	0	0	0	**5.5**	**G**	3
a1	**2100**	**115**	**12.02**									
a2	**60**	**95**	**0**									
a3	**0**	**-1**	**-1**									
[RSW]	00D0010D205FD0050009											
[SIV]	988698600	01-05-01	8:30	j	60	60	0	0	0	5.1	G	3
a1	480	109	10.56									
a2	120	95	14.85									
a3	180	82	2.65									
[RSW]	00D0010D2405D0070007											
[SIV]	988698600	01-05-01	8:30	j	60	60	0	0	0	1.5	G	3
a1	600	124	10.1									
a2	0	-1	-1									
a3	0	-1	-1									
[RSW]	00D0010D2405D007000B											
[SIV]	988698600	01-05-01	8:30	j	60	60	0	0	0	4.1	G	3
a1	540	112	19.17									
a2	120	83	5.66									
a3	60	76	0									
[MRBW]												
[SIV]	988698600	**01-05-01**	**8:30**	**j**	**0**	**0**	**1450**	**93**	-1	-1	G	
[MRBW]	03D0010D500AD0054200											
[SIV]	988698600	01-05-01	8:30	j	0	0	1450	90	-1	-1	G	

Table 6.1: *Section of MoniCa data acquired on May 1st 2001.*

The [RSW] detectors are the lane-specific detectors, identified by a 20-space hexadecimal code (bpshex). Besides the identification code, the most relevant attributes, displayed in **bold** in table 6.1, are: date, time-of-day (aggregation minute), the reliability indicator ('j' = reliable, 'n' = not reliable), amount of time (in seconds per minute) that the detector was in operation, amount of time (in seconds per minute) that the detector reported, percentage of time the detector was occupied by a vehicle and the congestion indicator ('G' = no congestion, 'C' = congestion, 'X' = inconclusive – for unreliable data). As mentioned in chapter 4, the congestion indicator is switched 'on', giving 'C', if five consecutive vehicles are detected with an individual speed that is less than 35 kilometres per hour and is switched 'off', giving 'G', if subsequently five consecutive vehicles with an individual speed higher than 50 kilometres pass the detector. Then there are three rows of vehicle categories; category a1 (vehicle length < 5.1

metres), category a2 (vehicle length > 5.1 and < 12.5 metres), and category a3 (vehicle length > 12.5 metres). For each vehicle category the attributes intensity (volume in vehicles/hour), 'mean speed' (in km/hour), and 'standard deviation of the mean speed' (in km/hour). At the end of the MoniCa data section displayed in table 6.1, two [MRBW] road detectors with their attributed data are shown. Road detectors are also identified by a 20-space hexadecimal code (bpshex), while the other most relevant attributes are: date, time-of-day (aggregation minute), the reliability indicator (again, 'j' = reliable, 'n' = not reliable), amount of time (in seconds per minute) that the detector was not in operation, amount of time (in seconds per minute) that the detector did not report, the intensity (volume in vehicles/hour) aggregated over all lanes in one driving direction, and the congestion indicator (again, 'G' = no congestion, 'C' = congestion, 'X' = inconclusive – is given when data is unreliable);

- *Select and organise lane-specific detector data*; organise each file in such a way that data acquired by each individual induction detector is represented per row and select only the detectors that acquire data on a lane-specific level. Furthermore, since each original unzipped file contains 1-minute aggregated information of possibly both lane-specific and road-detectors (aggregated over all lanes in one driving direction) only the lane-specific detectors should be selected and the acquired information per designated attribute in each row should be organised in the resulting file;

- *Transform the data sets into space-based data sets*; this step is a necessary requirement for dividing the files into two location-based sub-sets (Beekbergen and Hoevelaken). After completion of this step a reorganised section of data can be displayed as in table 6.2. The software package that was used for reorganising the data according to this step and the previous one was SPSS. The SPSS-code that was programmed to perform the job can be found on the next page.

00D0010D205FD0050005	10501	830	0	0	0	5.5	3	G	2100	115	12.0	60	95	0	0	-1	-1	0	3
00D0010D205FD0050005	10501	831	0	0	0	2.7	3	G	1020	123	5.18	0	-1	-1	0	-1	-1	0	3
00D0010D205FD0050005	10501	832	0	0	0	2.3	3	G	900	114	8.20	0	-1	-1	0	-1	-1	0	3
00D0010D205FD0050005	10501	833	0	0	0	2.8	3	G	1200	126	6.81	0	-1	-1	0	-1	-1	0	3
...				...										...					
00D0010D205FD0050009	10501	830	0	0	0	5.1	3	G	480	109	10.5	120	95	14.8	180	82	2.65	0	3
00D0010D205FD0050009	10501	831	0	0	0	3.6	3	G	660	106	18.6	120	82	4.95	0	-1	-1	0	3
00D0010D205FD0050009	10501	832	0	0	0	4.0	3	G	900	114	22.3	120	79	1.41	0	-1	-1	0	3
00D0010D205FD0050009	10501	833	0	0	0	4.6	3	G	540	124	16.0	60	82	0	180	87	2.31	0	3
...				...										...					
00D0010D2405D0070007	10501	830	0	0	0	1.5	3	G	600	124	10.1	0	-1	-1	0	-1	-1	0	3
00D0010D2405D0070007	10501	831	0	0	0	2.1	3	G	780	122	7.47	0	-1	-1	0	-1	-1	0	3
00D0010D2405D0070007	10501	832	0	0	0	2.1	3	G	780	130	15.0	0	-1	-1	0	-1	-1	0	3
00D0010D2405D0070007	10501	833	0	0	0	1.6	3	G	600	122	7.38	0	-1	-1	0	-1	-1	0	3

Table 6.2: *Section of reorganised MoniCa data, acquired on May 1st 2001.*

```
* Reorganisation of MONICA data.

SET MXMEMORY = 92000.
data list file 'BB0501.dat' list
 /rsw (A6) bpshex (A20) datum (A8) tijd (A5) status (A1) tijd1 (F3.0) tijd2 (F3.0) int (F5.0)
snelh (F5.0) intind (F1.1) snelind (F1.1) g (A1) x (F3.0) cong(F3.0).
* BPSHEX; lane detector starts with 00; road detector starts with 03.

if (rsw="[SIV]") bpshex = lag (bpshex).
execute.
if (rsw="a1") intcat1 = number (bpshex, F4.0).
if (rsw="a1") snelcat1 = number (datum, F4.0).
if (rsw="a1") stdcat1 = number (tijd, F4.2).
if (rsw="a2") intcat2 = number (bpshex, F4.0).
if (rsw="a2") snelcat2 = number (datum, F4.0).
if (rsw="a2") stdcat2 = number (tijd, F4.2).
if (rsw="a3") intcat3 = number (bpshex, F4.0).
if (rsw="a3") snelcat3 = number (datum, F4.0).
if (rsw="a3") stdcat3 = number (tijd, F4.2).
execute.

do if (rsw="a1" or rsw="a2" or rsw="a3").
compute bpshex = lag (bpshex).
compute datum = lag(datum).
compute tijd = lag (tijd).
compute status = lag (status).
compute tijd1 = lag (tijd1).
compute tijd2 = lag (tijd2).
compute int = lag (int).
compute snelh = lag (snelh).
compute intind = lag (intind).
compute snelind = lag (snelind).
compute g = lag(g).
if (g<> "C") cong = 0.
if (g = "C") cong = 1.
compute x = lag(x).
end if.
execute.

* remove road detector data.
select if (rsw<>"[SIV]" and rsw<>"[RSW]" and status="j").
save outfile 'mon.sav'.

get file 'mon.sav'.
compute uur = number(substr(tijd,1,2), F2.0).
compute minuut = number(substr(tijd,4,2), F2.0).
compute dag = number(substr(datum,1,2), F2.0).
compute maand = number(substr(datum,4,2), F2.0).
compute jaar = number(substr(datum,7,2), F2.0).
compute date = jaar * 10000 + maand * 100 + dag.
compute time = uur * 100 + minuut.

aggregate outfile *
 /break bpshex date time
 /int snelh intind snelind x = mean (int snelh intind snelind x)
 /g = first (g)
 /intcat1 snelcat1 stdcat1 intcat2 snelcat2 stdcat2 intcat3 snelcat3 stdcat3 cong =
 mean (intcat1 snelcat1 stdcat1 intcat2 snelcat2 stdcat2 intcat3 snelcat3 stdcat3 cong)
 /aantal = n.
save outfile 'BB0501.sav'.
```

- *Divide the data set in two location-based data sets*; the (geographical) transferability of the results produced by the models will be compared. Therefore the models that will be developed have to be calibrated on location specific datasets. Hence the data set is divided into a Beekbergen sub-set and a Hoevelaken sub-set by discrimination of the detector locations as given in appendix E. This procedure results in two data sub-sets for each day of the month of May 2001;

- *Remove bad-reporting induction detectors*; all detectors with an availability below 90 percent during the month May 2001 are removed (see appendix D);

- *Transform the data sets into time-based data sets*; a necessary step for easy removal of obsolete days (see the next two steps) and substitution of unreliable and missing data;

- *Remove the Saturdays and Sundays*; Saturdays and Sundays are not of interest because recurrent congestion is absent during those days, at least at the locations 'Beekbergen' and 'Hoevelaken';

- *Remove the over-represented days*; there are five Tuesdays, Wednesdays, and Thursdays in the data set present and since only four of each working day are needed this means that one Tuesday, one Wednesday and one Thursday has to be removed. The Tuesday, Wednesday and Thursday that contain the most unreliable and missing data are omitted. The resulting removed days are Tuesday May 29th, Wednesday May 23rd, and Thursday May 10th;

- *Split the data sets*; each of the location-based data sets is split into four location-based data sub-sets (representing a week worth of data of that particular location);

- *Substitute unreliable and missing data*; whenever data has been labelled as 'unreliable' or is missing, it will be replaced by the last known reliable data. This step leaves us with 8 data sub-sets that all have 5 (days) * 1440 (minutes) = 7200 entries.

- *Remove obsolete attributes*; take another look at table 6.2. All unreliable and missing data are 'recovered' and the files are now complete. This makes several attributes obsolete. The first attribute is detector identification. However, this attribute will remain present in the file, at least for now (it can be used whenever the file is reorganised following space base). The second attribute is date and can be removed (the files that incorporate which days of the month are known). Although rank (row number) can act as a proxy for time, attribute will not be removed for now for the same reason as detector identification (but then for time-based reorganisations). The next three attributes are obsolete and will be removed. Attribute ‘occupancy’ will be kept, obviously. The next two attributes have to go (column 19 is a translation of column 9 so one is completely redundant). Attribute ‘intensity’ (or volume) will also be kept, along with the attributes ‘mean speed’, and ‘standard deviation of the mean speed’; this goes for all vehicle categories. Finally, the attribute ‘congestion’ (‘1’ = congestion, ‘0’ = no congestion) will remain. This leaves us with the following data display:

00D0010D205FD0050005	830	5.5	2100	115	12.0	60	95	0	0	-1	-1	0
00D0010D205FD0050005	831	2.7	1020	123	5.18	0	-1	-1	0	-1	-1	0
00D0010D205FD0050005	832	2.3	900	114	8.20	0	-1	-1	0	-1	-1	0
00D0010D205FD0050005	833	2.8	1200	126	6.81	0	-1	-1	0	-1	-1	0
...				...			...			...		
00D0010D205FD0050009	830	5.1	480	109	10.5	120	95	14.8	180	82	2.65	0
00D0010D205FD0050009	831	3.6	660	106	18.6	120	82	4.95	0	-1	-1	0
00D0010D205FD0050009	832	4.0	900	114	22.3	120	79	1.41	0	-1	-1	0
00D0010D205FD0050009	833	4.6	540	124	16.0	60	82	0	180	87	2.31	0
...				...			...			...		
00D0010D2405D0070007	830	1.5	600	124	10.1	0	-1	-1	0	-1	-1	0
00D0010D2405D0070007	831	2.1	780	122	7.47	0	-1	-1	0	-1	-1	0
00D0010D2405D0070007	832	2.1	780	130	15.0	0	-1	-1	0	-1	-1	0
00D0010D2405D0070007	833	1.6	600	122	7.38	0	-1	-1	0	-1	-1	0

Table 6.3: *Section of re-reorganised MoniCa data, acquired on May 1st, 2001.*

- *Transform the data sub-sets*; the data sub-sets are being transformed into space-based data sub-sets. This is necessary in order to reorganise the files so that rank order is in accordance with traffic flow logic (the most upstream detector has the lowest rank, the detector that is hit as second one by the traffic flow has the following rank, etc.);

- *Reorganise the congestion data*; by following the traffic flow the location of the induction detector has the same logical order as the position in the database (the rank of the entry in the file) of data generated by that detector;

- *Isolate the congestion indicator data*; this data (as can be seen in the last column of table 6.3) will be used to analyse where the congestion phenomenon manifests itself and it will serve as target data, i.e. data that is used to calibrate and also (in a later stage) evaluate the models;

- *Rough analysis of the congestion data*; check out the congestion data to establish when congestion usually sets in. This procedure is necessary in order to define the morning and evening peak period. To make sure that the building up and breaking down periods also are included, at least half an hour before congestion sets in and half an hour after congestion has disappeared will be included into the peak periods. The morning peak period (a.m. peak) is defined as 06:00 – 10:59 hour, while the evening peak period (p.m. peak) is defined as 15:00 – 19:59 hour;

- *Filter the morning and evening peak data*; since recurrent congestion is only of interest, the data that were acquired during the morning and evening peak are selected, while the remaining periods are removed;

- *Analyse the congestion data in a graph*; set out the congestion data with on the horizontal axis the time path and on the vertical axis the detector identification number. Graphs can be produced for each working day by splitting up the working days of the week. Figure 6.1 provides the graph of the a.m. period of location Beekbergen, May 7th 2001. The remaining graphs of both peak periods of location Beekbergen as well as Hoevelaken can be found in appendices F – I;

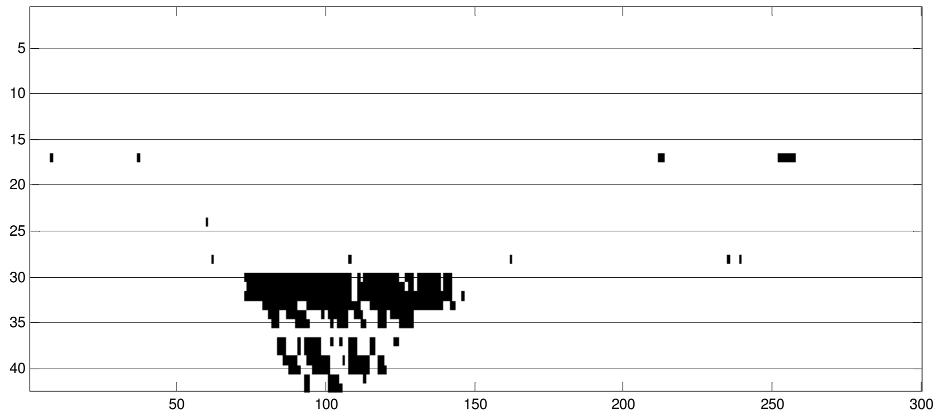

Figure 6.1: *Graph of congestion overview of the a.m. period of location Beekbergen, May 7th, 2001 (black = congestion).*

- *Identify the bottleneck detectors*; the identification procedure implies research to find out what detector has usually the first point in time to register congestion, i.e. the location where the onset of congestion takes place. For the morning peak of location Beekbergen, the detector with number 31 (originally with number 45 – see detector number coupling table displayed in appendix J) is usually the first detector to identify congestion, hence this detector is defined as the Beekbergen morning peak bottleneck detector. The identified bottleneck (or 'target') detectors for the remaining peak periods can also be found in appendix J. All target detectors, both for the morning and evening peak periods, are displayed in figure 6.2 (Beekbergen) and in figure 6.3 (Hoevelaken).

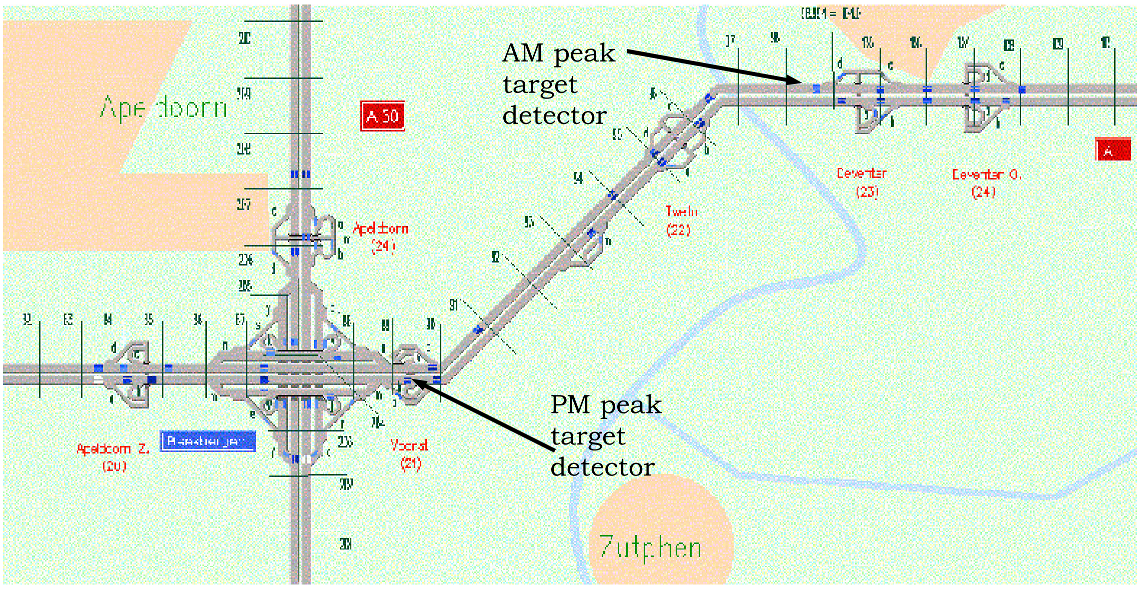

Figure 6.2: *The 'Beekbergen' AM and PM peak target detector.*

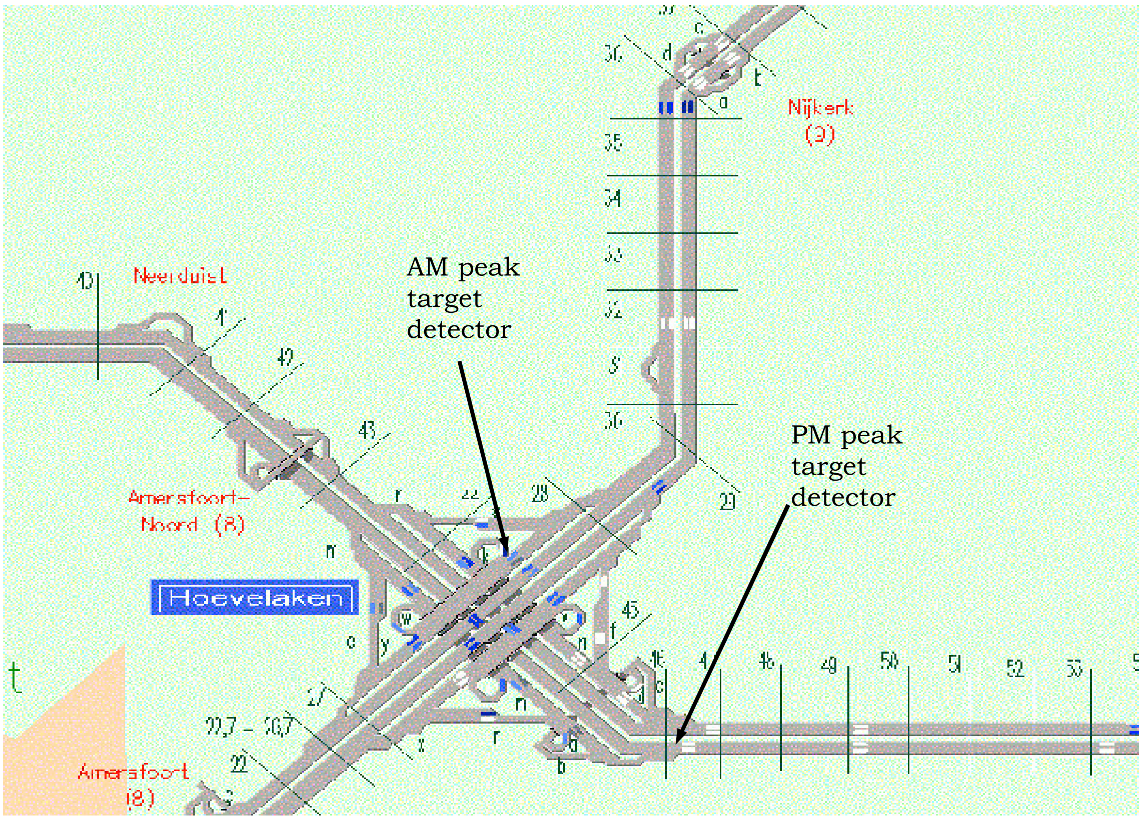

Figure 6.3: *The 'Hoevelaken' AM and PM peak target detector.*

- *Identify the relevant detectors*; after the bottleneck detector has been detected, relevant detectors are logically located upstream of the bottleneck detector. Additionally a few detectors downstream are selected to take back blocking congestion into account. These detectors have to be ranked up accordingly in the database. The detectors that are relevant for the Beekbergen morning peak are the detectors with – original – numbers: 44, 45 (bottleneck detector), 46, 49, 51, 52, 55, 57, 58, 61, 62, 67, and 68. Additionally, the down-stream detectors with numbers 42 and 43 were also included to take care of possible back-blocking congestion (final rank, appendix J);

- *Filter the data sets*; data coming from the identified detectors has to be selected and filtered so that only relevant data remains;

- *Remove obsolete attributes*; since the entries that hold attributes of which detector are known the rank entry can be used as proxy for identification number of the detector. This holds also for the time of day and date. After all, it is known that for the morning peak period of Beekbergen the first detector is the detector with original number 44. Depending on the sub-set the days of the month May 2001 that are represented in that sub-set are known. Furthermore, it is also know that the first 300 entries correspond with the 300 minutes (06:00 – 10:59) of the morning peak of the first represented day. This holds for all sub-sets of both Beekbergen and Hoevelaken. In short: entry rank is equivalent with time-of-day, date and identification number of the detector. This means that the first two columns of table 6.3 now can be removed, leaving 11 attributes per entry;

- *Isolate the bottleneck congestion indicator data*; congestion of the bottleneck detector is the only interesting congestion data since the congestion indicator of the bottleneck detector will act as target. The correct congestion data have to be isolated (the last attribute of detector with original number 45; equivalent with attribute 11 of rows 1501 to 3000 of the Beekbergen morning peak sub-sets – the second detector);

- *Remove the congestion indicator data*; after isolation of the congestion indicator data of the bottleneck detectors, the remaining congestion indicator data are now obsolete so they can be removed. Attribute (column) 11 of the sub-sets will be cut;

- *Reorganise the data sets into time-based data sets*; a necessary step is to make sure that each entry holds all relevant data per acquisition minute so that data can be fed time-wise to the models. This would be analogous to a model in operation. All 10 attributes per detector that were acquired during the same minute should be reorganised so that they can be found on one entry. To reach this goal the 10 remaining attributes acquired during the same minute by each detector, will be put consecutively in a row. This results in sub-sets that have 1500 entries (five working day peak periods of

300 minutes per day) and 10 * number of relevant detectors that represent the attributes (see figure 6.4 for a Beekbergen morning peak sub-set architecture description);

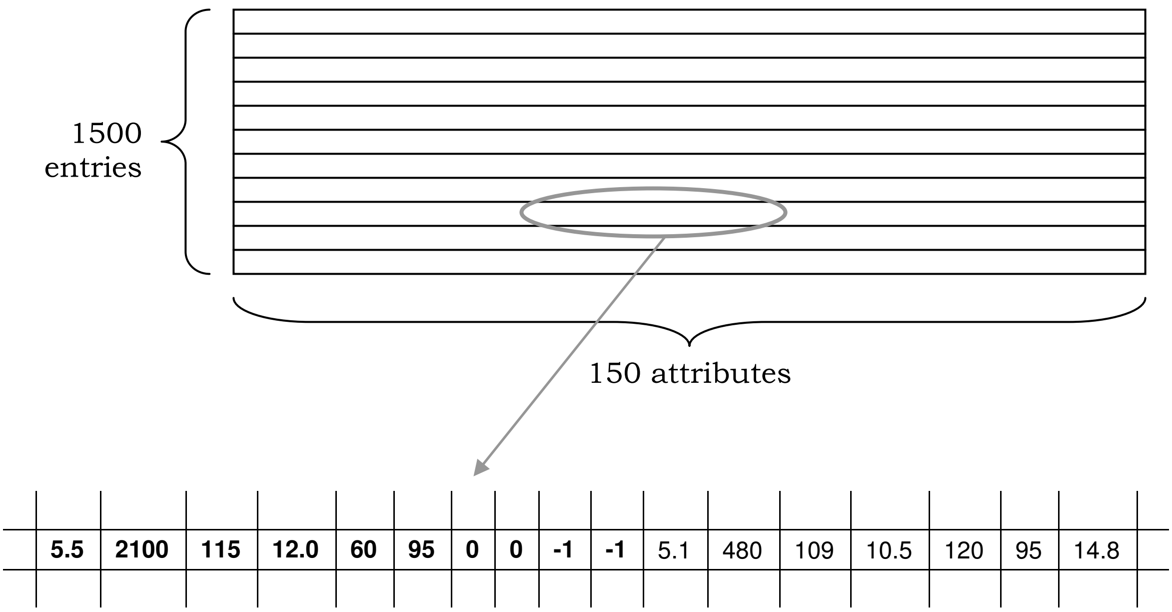

Figure 6.4: *Schematic display of a Beekbergen morning peak data sub-set: the bold numbers represent 10 attributes acquired through one detector. The first attribute represents the percentage of detector occupancy, the remaining nine represent the intensity, mean speed and standard deviation of the mean speed from the three vehicle length categories.*

- *Normalise the data sub-sets*; the data in the sets will act as input for the methods. During the model development phase certain features of input data will be assumed. One feature is that input data will be normalised on the [-0.8, 0.8] domain (see figure 6.5) so that every model can handle input data and that input data will be offered in a uniform condition to all methods.

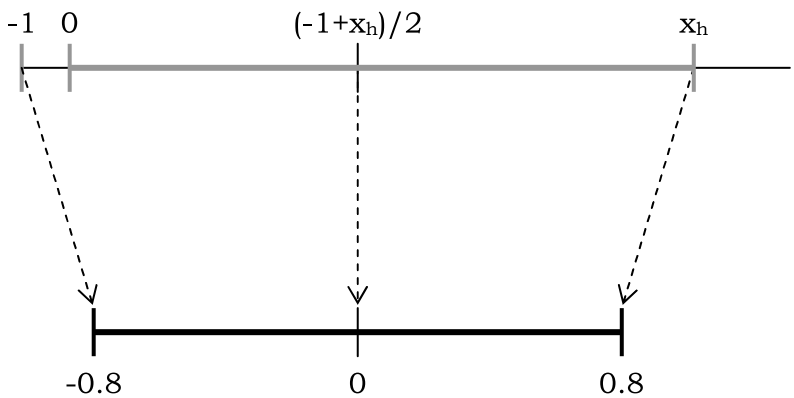

Figure 6.5: *Schematic display of data set normalisation (grey represents possible attribute values).*

Depending on the expected maximum value x_h for each attribute, the values of the data sub-sets are linearly normalised onto the [-0.8, 0.8] domain. For example, the expected maximum value of lane intensity is 2600 vehicles per hour. This means that an intensity of 1950 is normalised to 0.4. The generic accompanying formula to normalise x_i to y_i is given by (6.1):

$$y_i = 1.6 \cdot \left(\frac{x_i + 1}{x_h + 1} \right) - 0.8 \tag{6.1}$$

After performing all above-described steps there are 2 (locations) * 2 (peak periods) * 4 (weeks) = 16 data sub-sets, each holding 300 (minutes) * 5 (working days) = 1500 time entries. Each time entry has 10 (variables) * the number of selected detectors. Each data sub-set now also has an accompanying target data set coming from the bottleneck congestion indicator.

6.3.1 The aggregation level

The aggregation level during data acquisition by the MoniCa system through the MTM detectors is set on one minute. However, it is wrong to automatically assume that 60 seconds is the optimum aggregation level for data that is used to predict congestion. There is little to none literature that describes the influence of aggregation level of data acquisition to traffic prediction. Interestingly, one study was found that did so. Click *et al.* (1997) used several aggregation levels and showed that the optimum lies at one minute. Aggregation levels below one minute (20 seconds or 30 seconds) had a too chaotic nature to use for congestion prediction and two or five minutes aggregation led to too much averaging and hided the dynamics of the traffic flow alterations. Based on these conclusions the aggregation level of the MTM-MoniCa system should not have to be adapted, so it will remain one minute.

6.3.2 The target data

Data collected from the bottleneck detector will be used as target data. To make it even simpler, the congestion indicator data is the only data used for this purpose. The target data is translated: 'no congestion' into 0 and 'congestion' into 1. Each data sub-set now holds 1500 numbers and can be regarded as a vector containing 1500 units. The index number is linked to a particular minute of a working day (index number 1 represents Monday 6:00 a.m., whereas index number 363 represents Tuesday 7:02 a.m.). By shifting the index numbers with T spaces to the left, the target vector with a prediction horizon of T minutes is obtained. An example:

Origin = [0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, ...]

The index is shifted by 5 spaces and then becomes

Target = [0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ...]

which is now the target vector with a 5-minute prediction horizon.

Since the models will be assessed on their predictive performances within the short-term horizon, the term 'short-term horizon' has to be defined. Actually, the models will be assessed on several time horizons, i.e. 5, 10, 15, 20, 25, and 30 minutes ahead. This results in six target vectors and since the 0-minute performances have to be checked this adds up to seven target vectors per data sub-set.

In conclusion, the number of target vector is equal to: 16 (data sub-sets) * 7 (target vectors) = 112 target vectors.

Due to the character of the activation functions of several artificial neural networks (see chapter 3), the target values have to be normalised onto the [-0.8, 0.8] domain. Since the target can have the binary values {0, 1}, normalisation is rather straightforward: 0 becomes –0.8 and 1 is normalised to 0.8 (see figure 6.6).

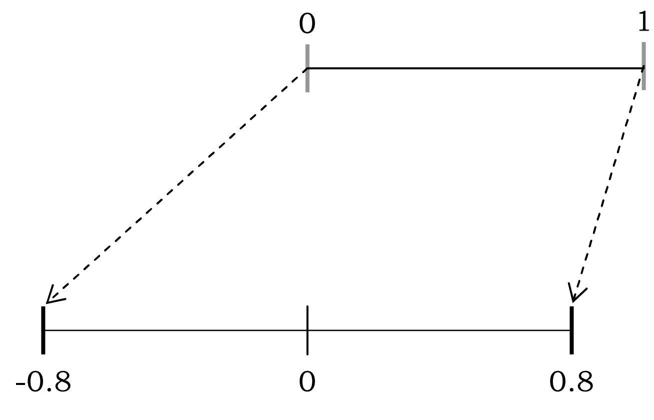

Figure 6.6: *Schematic display of target data normalisation.*

6.3 Outlook

To give an impression of the task at hand a data sub-set with target data is schematically displayed (figure 6.7). One has to keep in mind that every black dot represents a detector that in its turn represents the traffic flow state described by 10 attributes.

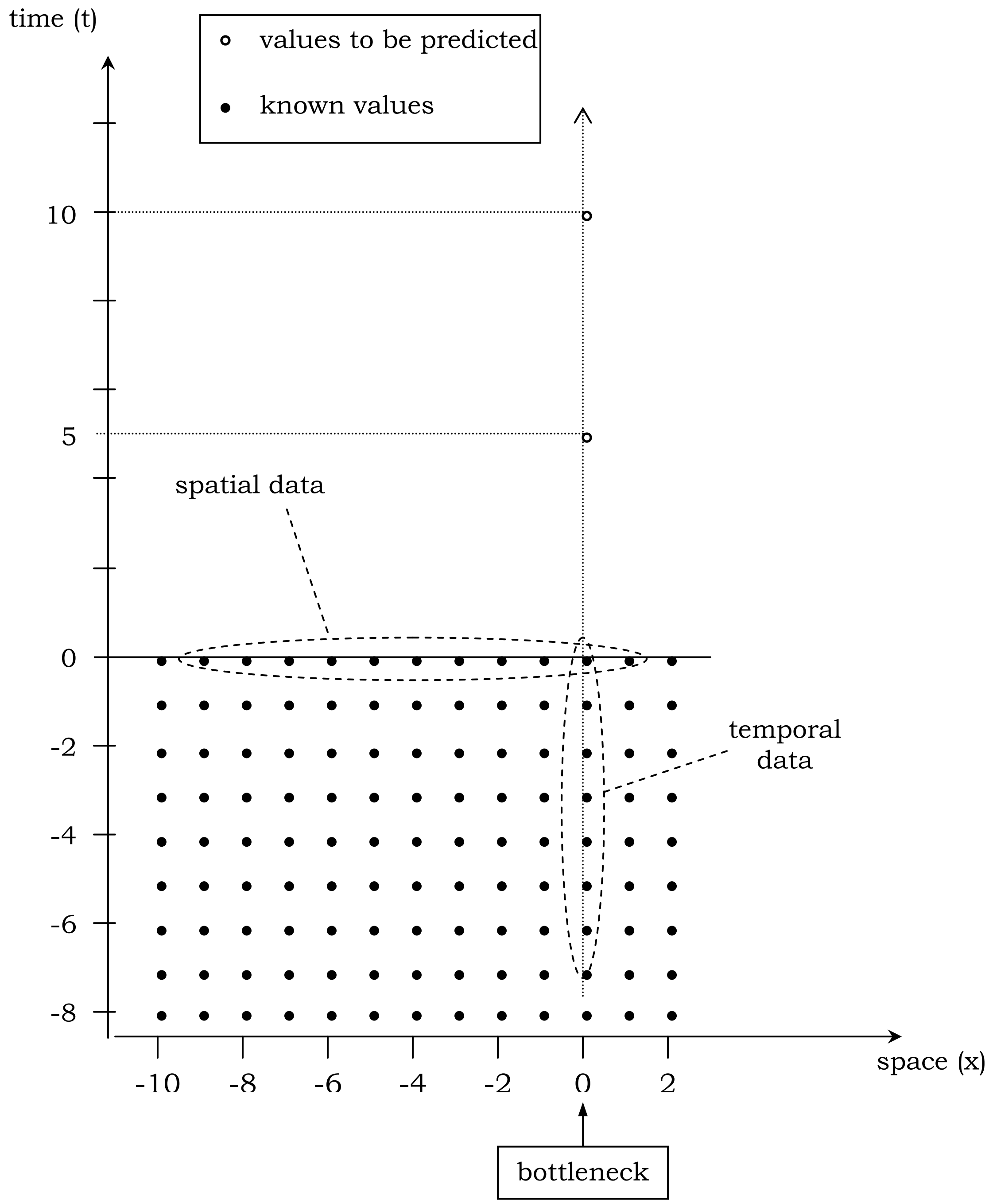

Figure 6.7: *Schematic display of a data sub-set with target data (negative space numbers represent detectors upstream of the bottleneck).*

The consequence of all previous described procedures is that seven methods have to be developed into models for two peak periods per designated location resulting in 28 models of which the performances will be assessed for seven prediction horizons and four rotating sub-sets as evaluation sub-set (while the remaining three sub-sets act as calibration data sets). Some of the models can be developed straightforward (the Naïve and the Multi Linear Regression models), the remaining ones have to be explored further during the development phase to find a (near) optimum model architecture with accompanying learning rules/parameters. Hence, the model development that is described in the next chapter can be regarded as a time-consuming task.

CHAPTER 7

Model development

"There are many methods for predicting the future. For example, you can read horoscopes, tea leaves, tarot cards, or crystal balls. Collectively, these methods are known as 'nutty methods'.

Or you can put well-researched facts into sophisticated computer models, more commonly referred to as 'a complete waste of time'."

In: 'Dilbert Future'
by Scott Adams

7.1 Introduction

The chapter reports on the model development that was conducted using the methods described in chapter 3 and the acquired data described in chapter 4 that was pre-processed in the previous chapter. This resulted in four data sets:

- The morning peak data set of Beekbergen;
- The evening peak data set of Beekbergen;
- The morning peak data set of Hoevelaken;
- The evening peak data set of Hoevelaken.

All data sets contain four data sub-sets, each representing the peak period of a working week. This chapter describes how the models were developed using those sub-sets. First, information is given on the construction process of the test data set that will be used to select several parameters that are necessary to develop and describe a model, e.g. the architecture of artificial neural networks. Guidance through the development process for one data set only is provided, i.e. for the morning peak data set of Beekbergen. This procedure is chosen because the description of the development of all data sets would not add significantly to the understanding of the process itself; it would merely add to the number of pages of this thesis.

7.2 Construction and use of the test set

Apart from the naïve models and the Multi Linear Regression models, all other methods have several parameters that describe the 'structure' (e.g. the architecture of an artificial neural network) of the model; see also chapter 3. The values of these parameters need to be established to optimise the models in such a manner that they will produce the maximum performance possible or, in other words, will minimise the model's generalised error E^G.

To find the optimum values of the parameters, a test set of data to determine the change of output error $E^{C(x1, \dots, xN)}$ of each model with changing parameters $x1, \dots, xN$ is needed. To come to a test set, a fraction (about 10 percent) of input vectors out of the data sets at our disposal was randomly selected and the jack-knife method was used to assess the models. Like cross-validation, this method uses a substantial part of a data set to calibrate the model and one small portion to estimate the error. By leaving out a separate part of the data set each time, the remaining bulk of the data set is used to calibrate the model, while the omitted part is used to determine the error it produces. This way, one can, after error estimation of all omitted parts of the total test data set, estimated errors $E^{C(x1, \dots, xN)}$ can be compared (figure 7.1).

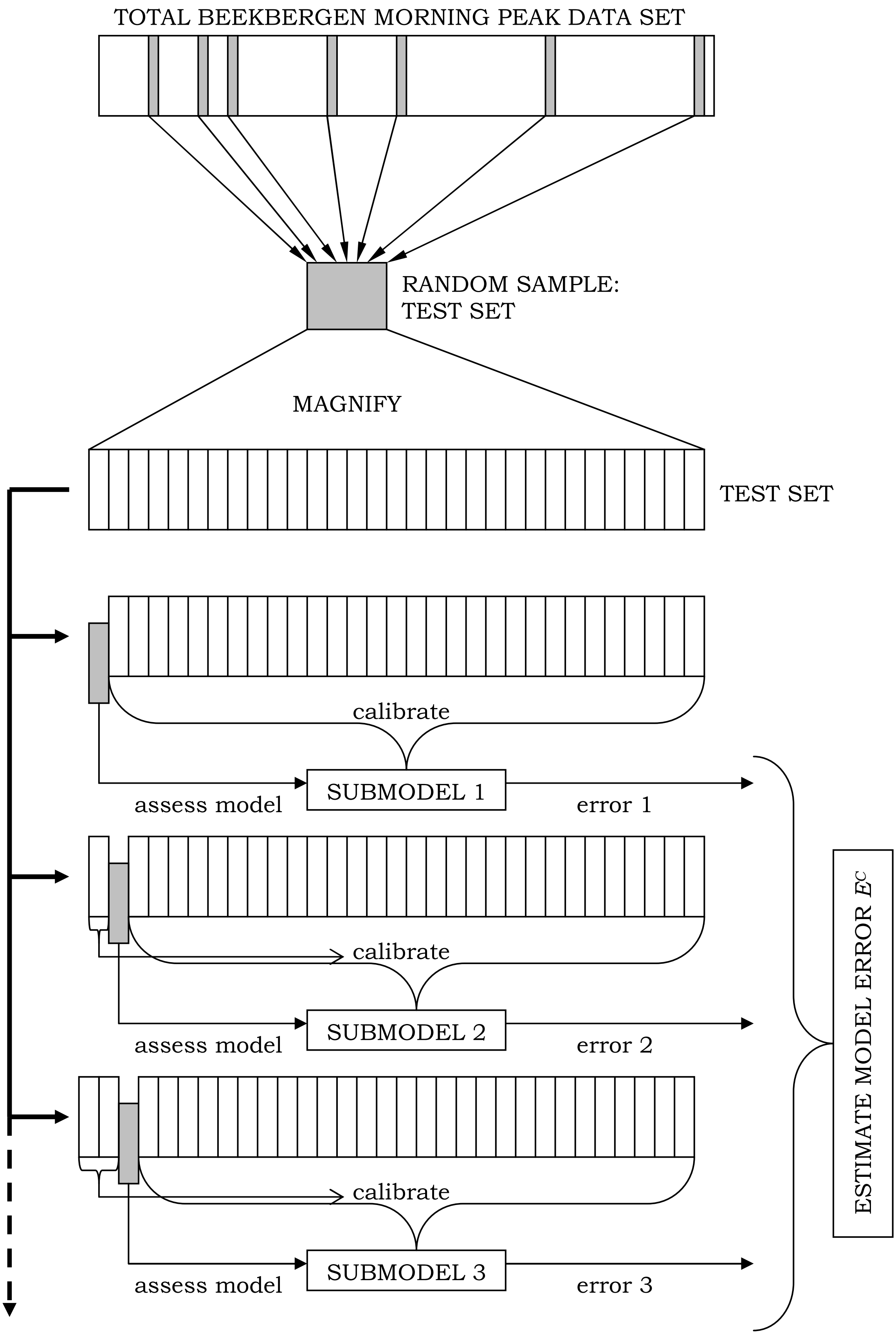

Figure 7.1: Schematic overview of the jack-knife procedure.

The parameter values of the model that produced the lowest error are now selected to describe the structure of the model (e.g. the neural network architecture for a MLF neural network). After the model is built it will be calibrated with the original data subsets (starting with the Beekbergen morning peak subsets); three weeks of data (three subsets) are used to calibrate the model, while one week of data (one subset) is used as the validation data set. Subsequently, the data subsets used in the primary validation score are used as the validation data subset according to the cross-validation scheme.

7.3 Naïve models

The model development of the data set into naïve models is simple. Only data collected from the bottleneck detector is used. To make it even simpler, only the congestion indicator data is used. As already described in the previous chapter the data is normalised by translation 'no congestion' into –0.8 and 'congestion' into 0.8. Each target data subset now holds 1500 numbers and can be regarded as a vector containing 1500 elements. The index number is linked to a particular minute of a working day (the element with index number 1 represents Monday 6:00 pm). By shifting the index numbers with t spaces to the left the target vector with a t-minute prediction horizon is obtained. An example; for t = 5 minutes:

$$O(rigin) = [-0.8, -0.8, -0.8, -0.8, -0.8, -0.8, -0.8, -0.8, 0.8, 0.8, 0.8, \ldots]$$

The index is shifted by 5 spaces (minutes) to the left and hence becomes:

$$T(arget)^{(t=5)} = [-0.8, -0.8, -0.8, 0.8, 0.8, 0.8, 0.8, 0.8, 0.8, 0.8, 0.8, \ldots]$$

which is now the target vector with a 5-minute prediction horizon.

The model has to be fed with input data. Since this is the naïve model this means that O is the input data vector *as well* as it is the result vector, $R(esult)^{(t=5)}$. If $R^{(t=5)}$ is subtracted from $T^{(t=5)}$ the resulting difference between target and result can be defined as the error vector $E(rror)^{(t=5)}$ after dividing the element's values by 1.6 (in order to re-normalise the values). This is graphically be displayed in figure 7.2 as a hypothetical case of a peak period of 5 hours with a target vector $T^{(t=5)}$ (with a 5-minute prediction horizon), a result vector generated by the naïve method $R^{(t=5)}$ (that also represents the state of the congestion indicator) and an error vector $E^{(t=5)}$.

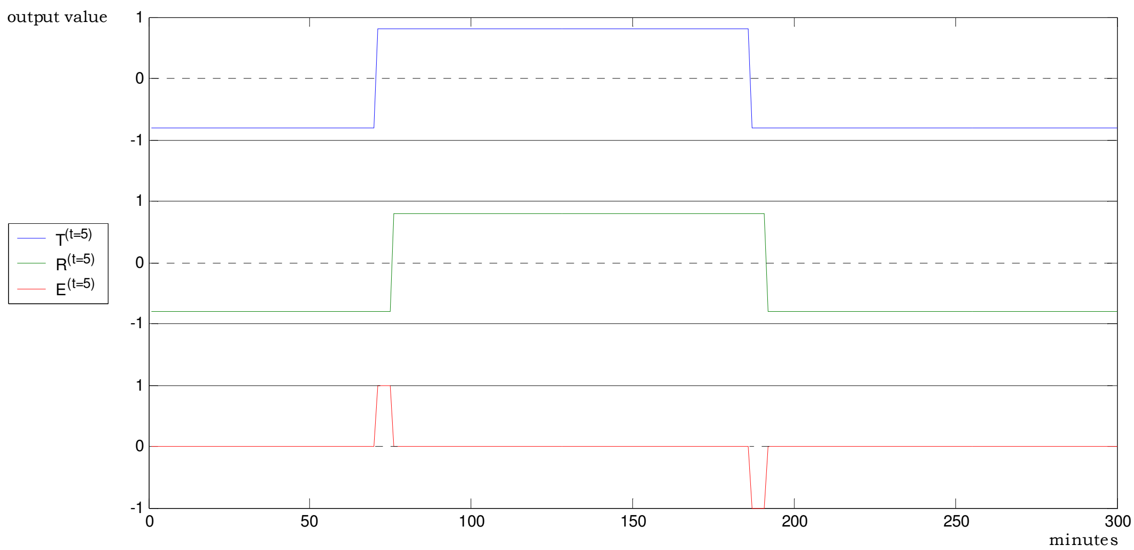

Figure 7.2: Assessment of the naïve method with a prediction horizon of 5 minutes: target vector (top), result vector (middle) and error vector (bottom). The horizontal pieces of the error vector at y = 1 and y = -1 have a duration of 5 minutes, equal to the prediction horizon (*hypothetical situation*).

So, *O* is used as a model input to predict the congestion status of the stream at the bottleneck location with a 5-minute horizon and is equivalent to the resulting $R^{(t=5)}$. This process can be done for any number of *t* minutes, keeping in mind that the prediction horizon should not exceed the shortest 'no congestion' period after 6:00 hours and before 11:00 hours in the morning. As mentioned in chapter 6, prediction horizons of 5, 10, 15, 20, 25, and 30 minutes will be assessed. Additionally, the 0-minute prediction horizon will be used to establish the method's performance in estimating the current state of the traffic flow with regard to congestion at the bottleneck detector location; it goes without saying that the error of the naïve model at the 0-minute horizon is equal to 0.

7.4 MLR models

Input data for the MLR model is collected through all relevant detectors. For the morning peak period of the Beekbergen location this means, as already explained in chapter 6, data gathered by all dual induction loops upstream of the bottleneck detector and two dual induction loops downstream, to take upstream congestion into account. This results in 1-minute time slices of 15 detectors * 10 variables = 150 input variables. Since there is 1 output variable (the congestion indicator of the bottleneck detector with original number 45) four input matrices of 150 * 1500 [300 minutes peak period for five week days] elements and four target vectors of 1500 elements representing four work day weeks are obtained.

Three input matrices are combined (placed behind each other) to a resulting 150 * 4500 matrix and the accompanying target matrices undergo the same procedure resulting in a 4500 element vector. These matrices are then used according to formula (3.4) and so the resulting matrix *C* that holds the calibrated multiplier indices is obtained and so is, in fact, our MLR model.

During the evaluation phase the MLR model is used in combination with the remaining input matrix (the evaluation matrix). If the evaluation matrix with *C* is multiplied a result vector $R^{(t=T)}$ will be obtained. Ideally, the result vector $R^{(t=T)}$ should be equivalent to the remaining target vector $T^{(t=T)}$. The resulting vector $R^{(t=T)}$ is subtracted (element by element) from the target vector $T^{(t=T)}$ and this produces an error vector $E^{(t=T)}$ that is used to determine the model's error. This procedure is then repeated four times by means of cross-evaluation, whereby each time a different input matrix serves as evaluation matrix.

7.5 ARMA models

Input data for the ARMA(f, g) model are collected through the bottleneck detector. The ARMA model uses spatial data from the bottleneck detector to calibrate the model, according to formula (3.7). The number of input variables is restricted to six, due to computer processing time limitations and the time series analysis character (otherwise this would lead to the development a state-space model). The input variables are 1-minute aggregates of:

- Occupancy (aggregated over all three vehicle categories);
- Intensity (of the first vehicle category);
- Speed (of the first vehicle category);
- Deviation of speed (of the first vehicle category);
- Speed (of the second vehicle category);
- Speed (of the third vehicle category).

The first four variables are obvious, the latter two were chosen due to the thought that, if the traffic stream is near congestion state, the presence of large vehicles will increase the chaotic effect, mainly due to their lower speed in comparison with vehicles of the first category.

The identification of the lag and order index that will provide the best results is a time consuming task. In order to come to the identification of the proper lag and order index, a data test set is constructed that consisted of the test set of data possibly coming from all available data input sets and accompanying data target set (with several prediction horizons), as described in section 7.2. This test set is used to assess the calibrated ARMA models and thus to establish the values of lag and order that provide the lowest error.

Firstly the ARMA(0,1) model was assessed with the jack-knife procedure, as described in section 7.2. The error result of each calibrated and validated ARMA(0,1) model is stored. All error results are then combined by taking the mean. This error value is then put in a table and serves as ARMA(0,1) result. Subsequently, the ARMA(0,2) model was built. The same procedure was carried out: use the test set with jack-knife procedure and store all results. Consequently, the mean is determined and put in a table where it serves as the ARMA(0,2) result. The procedure was repeated to build, calibrate and test ARMA(0,2) to ARMA(0,12) models.

The next step is to alter the value for lag from 0 to 1. Again, the routine described above is carried out for the ARMA(1,1) to the ARMA(1,12) models. After that, the value for lag is also changed to 2 and subsequently, after the same routine, to 3. All values are stored in the table that can be visualised as in figure 7.3.

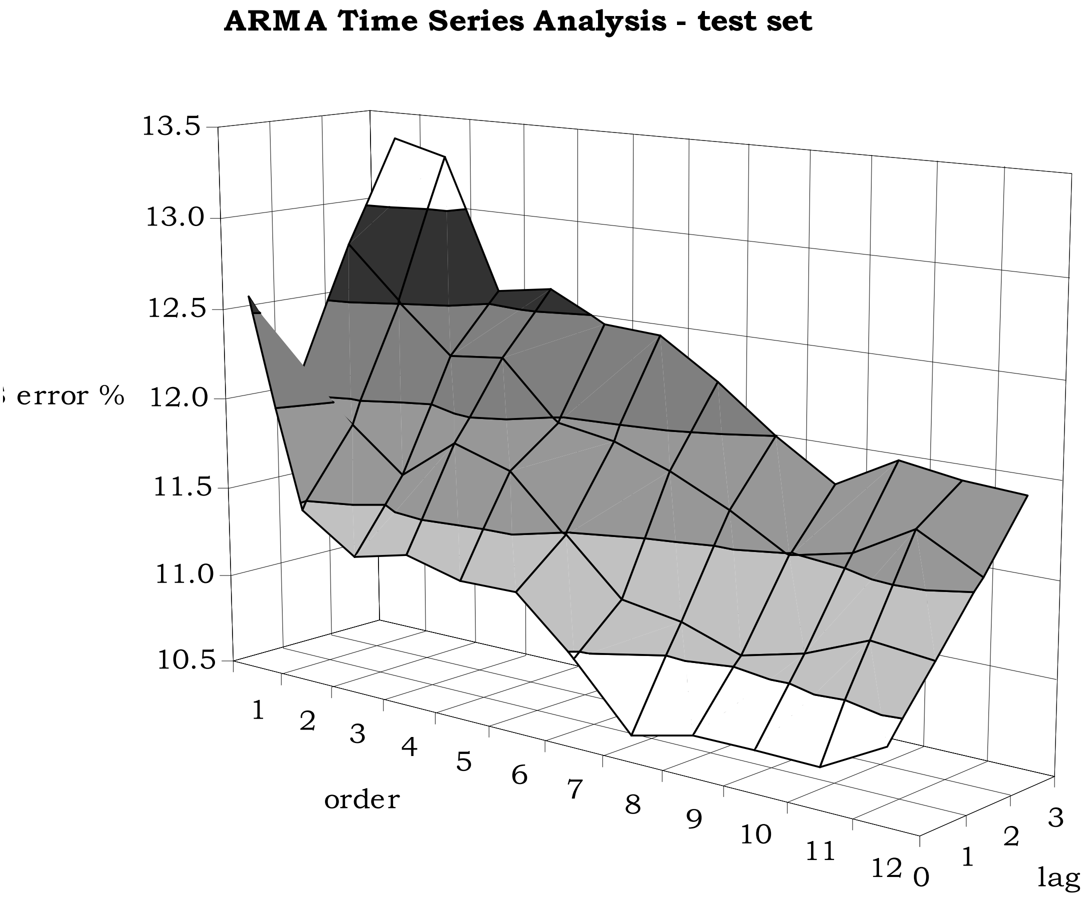

Figure 7.3: ARMA time series analysis – mean error percentage of the test set depending on order and lag.

In order to find the values of lag and order that are expected to produce the best results, 4 * 12 = 48 ARMA models were built. Each of these 48 models was then calibrated and tested about 400 times, thus generating an error term displayed in figure 7.3 as one dot on the surface graphic. After the values of the 48 dots were established it can be seen that the optimum for the ARMA time series lag and order is at (0,8) leading to the ARMA(0,8) model as the model with the optimal lag and order.

7.6 MLF models

The input data that were used for the Multi Linear Regression models are the same that will be used for Multi Layer Feedforward neural networks. Again, relevant data with respect to the congestion state of the traffic stream at the bottleneck detector location were collected through 15 dual induction loop detectors. Since each detector records 10 variables per minute, this results in 150 1-minute aggregated variables. This means that there is one vector of 150 elements for each minute during the peak period giving 6000 minutes of working day peak period minutes during the month of May 2001.

The same test data set that was used to select the optimum values of lag and order for the ARMA models described in section 7.5 was used. The test data set is used analogous to the time series analysis model development, by using the jack-knife method to select the optimum values for the structure (number of neurons in the hidden layer of the MLF and the number of training epochs – see chapter 3).

Five basic MLF structures were built. The architectures of these models can be described by the number of neurons per layer (first the number of input neurons in the input layer, then the number of hidden neurons in the hidden layer, and finally the number of output neurons in the output layer). The basic MLF architectures have a 150 – X – 1 architecture, with X = 2, 4, 6, 8, 10.

The test set is divided into a large set and a small set. Each 150 – X – 1 MLF is calibrated using the large set for a number of predefined learning epochs, i.e. 10, 20, 30, 40, 50, 60, and 70 learning epochs. Subsequently, the trained MLF is assessed by the small set. After storing the outcome, the test set is once again divided into a large set and a small set; the small set is totally different from the previous small set. The 150 – X – 1 MLF is calibrated using the new large set for the same number of predefined learning epochs. The trained MLF is assessed by the new small set. This procedure is repeated until the total test set has been used as assessment set (figure 7.1). After determining the mean of the error outcomes, it is put in a table that is represented by a dot on the surface graphic depicted in figure 7.4.

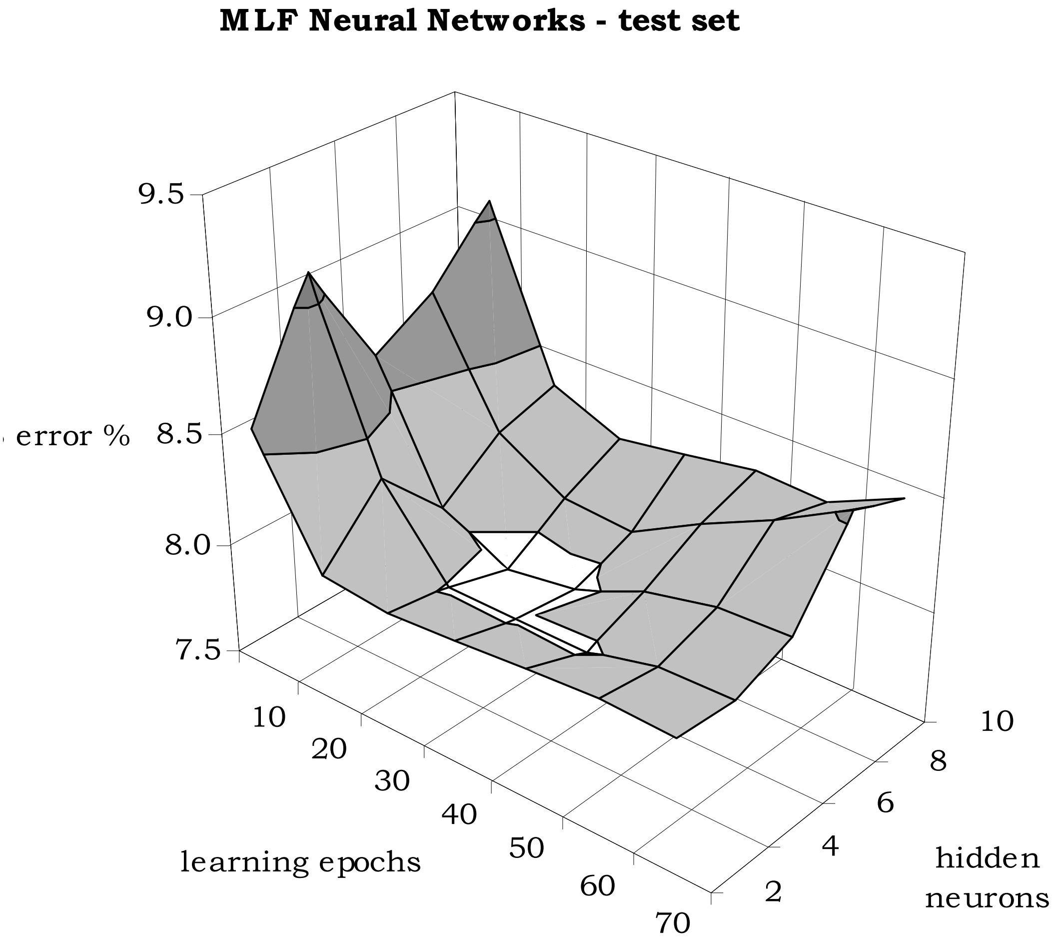

Figure 7.4: MLF neural networks – mean error percentage of the test set depending on learning epochs and hidden neurons.

All in all 5 * 7 = 35 MLF models were built to find the values of hidden neurons and learning epochs that are expected to produce the best results. Each of these 35 models was then calibrated and tested about 400 times, thus generating an error term displayed in figure 7.3 as one dot on the surface graphic. After the values of the 35 dots were established it can be seen that the optimum for the MLF neural network architecture and learning epochs is at (6, 30) leading to the 150 – 6 – 1 MLF architecture that has to be trained for 30 learning epochs.

7.7 RBF models

The procedure for obtaining the optimum number of hidden neurons in the hidden layer of the RBF model and the optimum amount of learning epochs is almost identical to the one described for the MLF neural network model. The difference is the number of hidden neurons and of learning epochs that were assessed. Six RBF model architectures were developed (with 2, 4, 6, 8, 12, and 16 hidden neurons) and each model was trained for 9 separate learning epoch periods (20, 30, 40, 50, 60, 70, 80, 100, and 150 epochs). The resulting surface plot is displayed in figure 7.5.

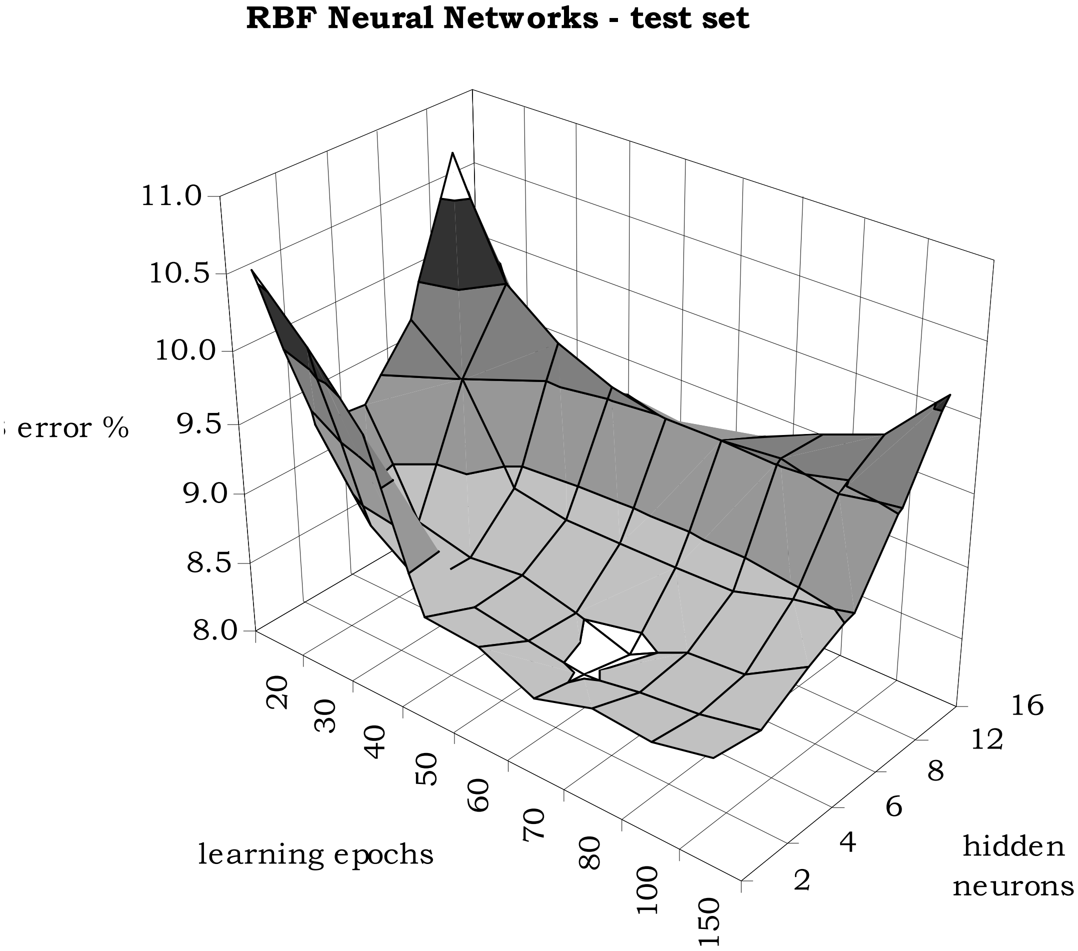

Figure 7.5: RBF neural networks – mean error percentage of the test set depending on learning epochs and hidden neurons.

This means that 6 * 9 = 54 RBF models were developed in order to establish the values of hidden neurons and learning epochs that are expected to produce the best outcomes. Each of these 54 models was then calibrated and tested about 400 times, thus generating an error term displayed in figure 7.5 as one dot on the surface graphic. As can be seen in the graph displayed in figure 7.5, the optimal architecture is the 150 – 6 – 1 RBF architecture, which has to be trained during a period of 70 learning epochs.

7.8 Elman models

The procedure for obtaining the optimum number of hidden neurons in the hidden layer of the Elman model and the optimum amount of learning epochs is, again, almost identical to the one described for the MLF and RBF neural network model. The difference is the number of hidden neurons and of learning epochs that were assessed. Five Elman model architectures were developed (with 2, 4, 6, 8, and 10 hidden neurons) and each model was trained for 8 separate learning epoch periods (50, 80, 100, 150, 200, 250, 300, and 400 epochs). The resulting surface plot is displayed in figure 7.6.

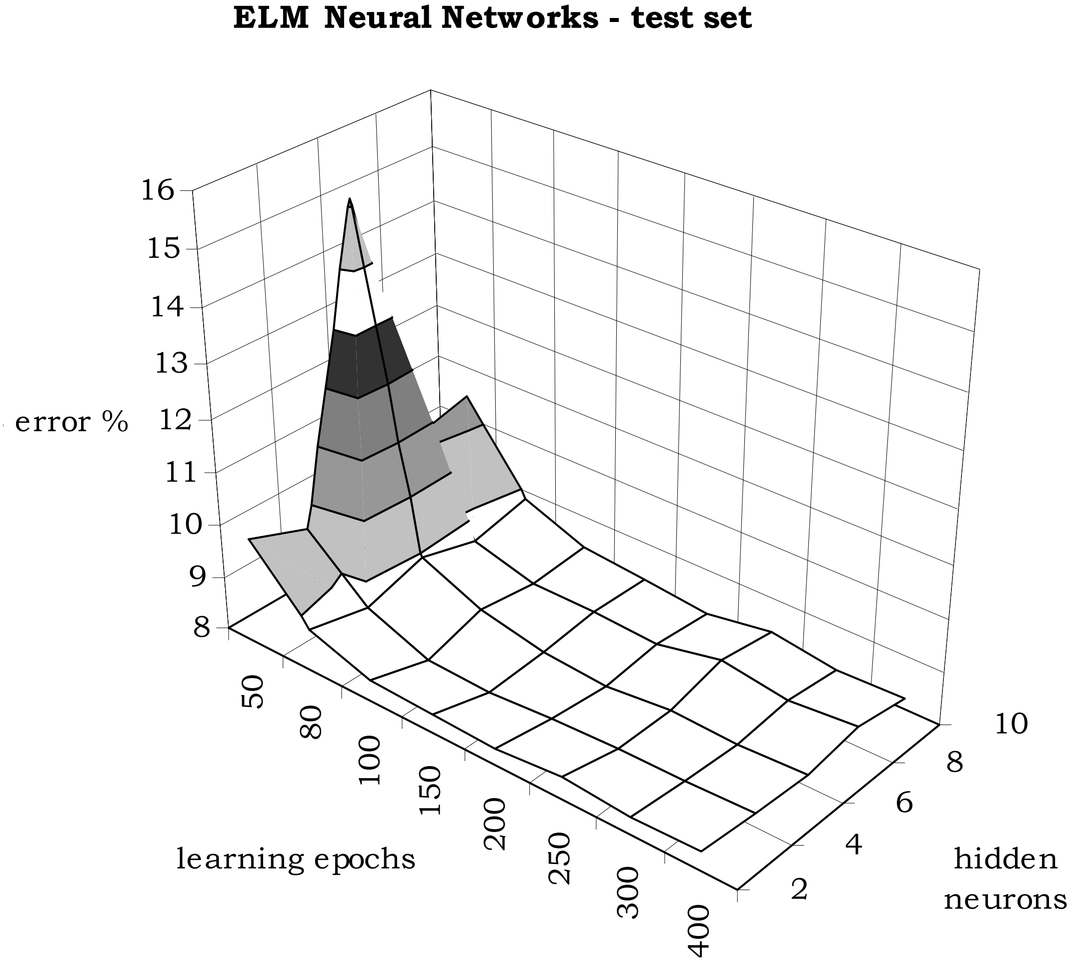

Figure 7.6: ELM neural networks – mean error percentage of the test set depending on learning epochs and hidden neurons.

A total of 5 * 8 = 40 Elman models were developed to find the values of hidden neurons and learning epochs that are expected to produce the best results. Each of these 40 models was then calibrated and tested about 400 times, thus generating an error term displayed in figure 7.6 as one dot on the surface graphic. After the values of the 40 dots were established it can (barely) be seen that the optimum for the Elman neural network architecture and learning epochs is at (6, 200) leading to the 150 – 6 – 1 Elman architecture that has to be trained for 200 learning epochs.

7.9 SOM models

Self Organising Map neural networks are not as straightforward as the other neural networks. First of all, there is no set procedure for finding the optimum model architecture, since the output layer can be a linear layer of neurons or a two-dimensional structure. If it is a two-dimensional structure there is a choice between a hexagonal and a rectangular grid. In addition, with a binary target, one has to find out which of the output neurons on a layer or grid are considered as firing or winning, i.e. which output neurons will count as ‘congestion’ and which ones will not. Only linear SOM neural networks were used, because the optimal architecture problem at Self Organising Maps is a four-year study subject in itself.

A systematic search for the optimum SOM architecture is handled by starting with a linear output layer of two neurons, checking the error that it generates, adding one neuron to the output layer, checking the error it now generates, and repeating this procedure. Checking is done by visually comparing the winning neurons with the congestion target vector. This quest could be quantified but with visual inspection one can more easily check if the pattern is actually reproduced by the SOM (see figure 7.7).

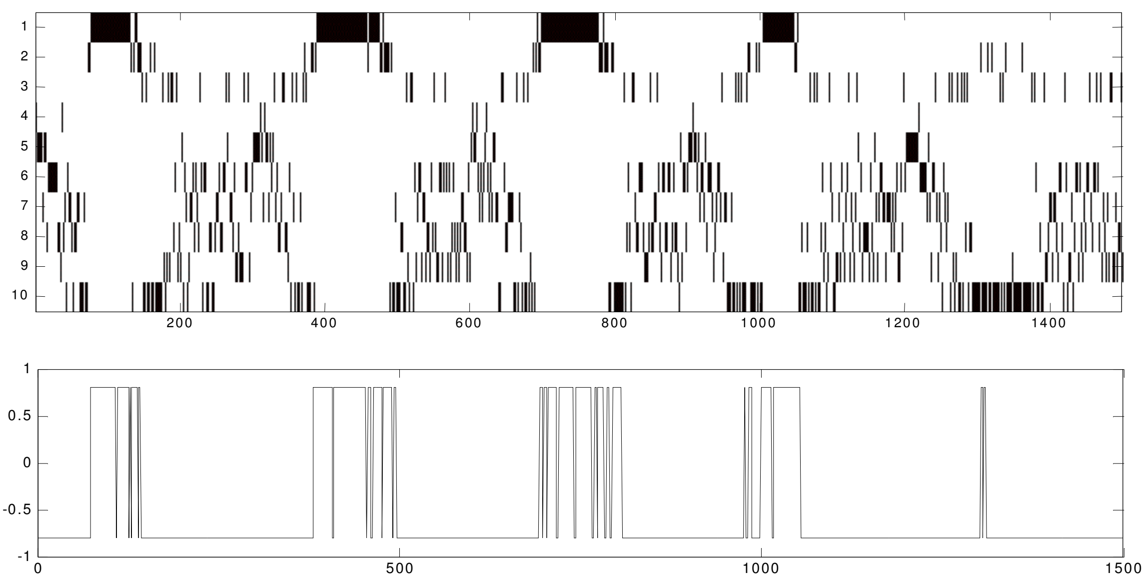

Figure 7.7: The first in combination with the second neuron of the trained linear SOM of 10 neurons (top) bear resemblance to the target vector (bottom).

After visual inspection, the linear SOM of 10 neurons was selected as most promising SOM neural network. The first as well as the second neuron is marked as ‘congestion state’ neuron and the output it generates will be compared with the target vectors.

7.10 FL models

Input data for the Fuzzy Logic models are collected through the bottleneck detector. The Fuzzy Logic model uses only data from the bottleneck detector to calibrate the model. The number of input variables was restricted to four, due to computer processing time limitations. The input variables are 1-minute aggregates of:

- Occupancy (aggregated over all three vehicle categories);
- Intensity (of the first vehicle category);
- Speed (of the first vehicle category);
- Deviation of speed (of the first vehicle category).

More than 90 percent of all vehicles are in the first vehicle category thus describing the first category is the best approximation of the total traffic stream for a description.

Again, the test set is used to find the optimum values of the parameter that is used to describe the construction of the ANFIS Fuzzy Logic model; the number of learning epochs. The model was trained for a number of epochs, after which jack-knifing was used to assess the model. As can be seen in figure 7.8, the optimum number of learning epochs is 125.

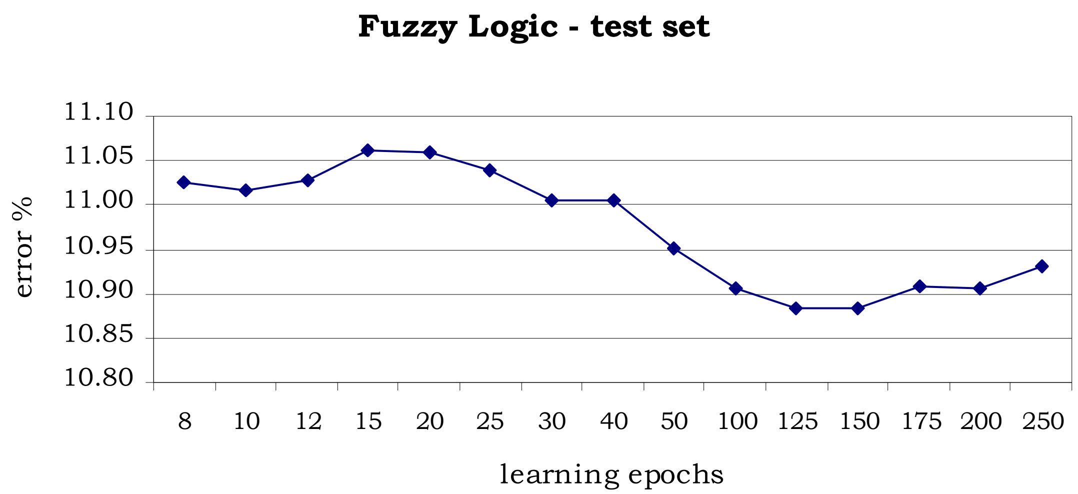

Figure 7.8: Fuzzy Logic – mean error percentage of the test set depending on learning epochs.

7.11 Calibration and validation

The optimum values for all model constructions are established. Each method is now developed into several models that need to be calibrated (with the exception of the naïve models). As mentioned before, cross-validation is used to assess the models.

For each prediction horizon four identical models are developed according to the optimum parameter values. Every model is calibrated using three Beekbergen morning peak sub-sets, while the remaining sub-set is used for validation (see figure 7.9).

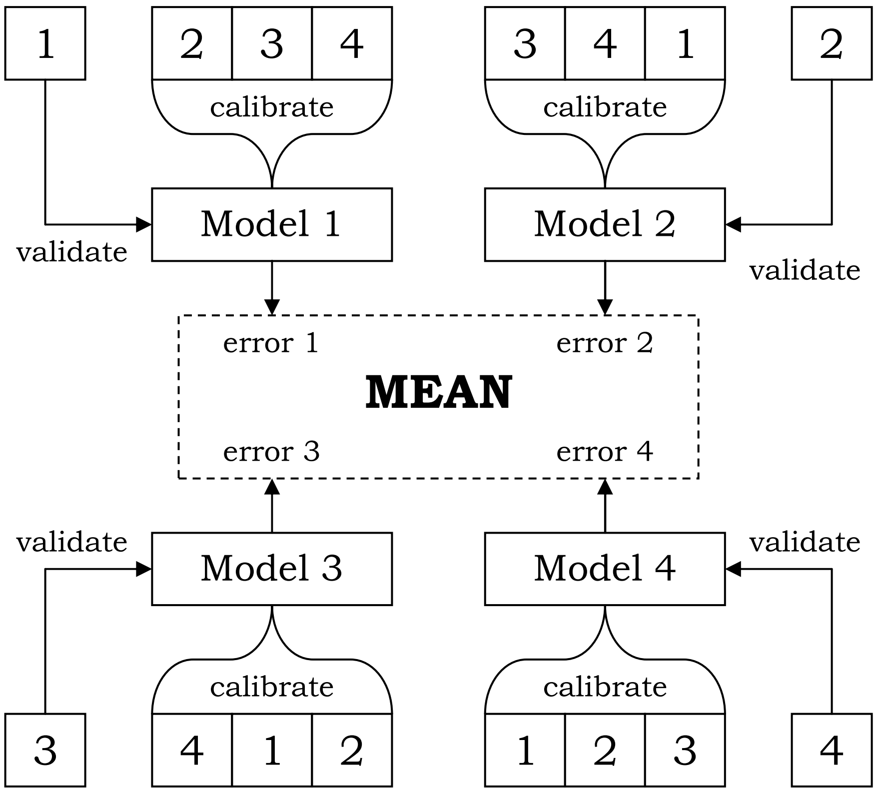

Figure 7.9: The cross-validation scheme.

Four identical MLF models that will be used to evaluate the MLF method for the 5-minute prediction horizon are given as an example (figure 7.8). The model has a 150 – 6 – 1 architecture of neurons. The optimum number of training epochs is 70. Sub-sets 2, 3, and 4 are used to train the first MLF model for 70 epochs. After this, the model is completed. The model is assessed by feeding sub-set 4 to the model. The 1500 outcome elements are now compared with the 1500 target elements, one by one. The total error that was generated by sub-set 1, the validation sub-set, is stored. This procedure is repeated for the second MLF model, the difference being that sub-sets 3, 4, and 1 are used to train the model (again, for 70 epochs). Then sub-set 2 is used as validation sub-set and the total error it generates is stored. The same procedure is followed for the third and fourth MLF model (hence the 'cross' in cross-validation). After all four sub-sets have served as validation sub-set, the total model error is estimated by computing the mean of the four stored error terms. This mean value is now the total model error that the MLF model has generated for the 5-minutes prediction horizon.

7.12 Conclusion

The routine described in the example in the previous paragraph has to be carried out for all prediction horizons, for all methods. This means that 6 methods (all methods except for the naïve method) * 7 prediction horizons (0, 5, 10, 15, 20, 25, and 30 minutes) * 4 validation models = 168 models that need to be calibrated and 196 models that need to be validated (here the naïve models are included). The results are described in the next chapter.

CHAPTER 8

Results

"There are no facts, only interpretations."

Friedrich Nietzsche

8.1 Introduction

In this chapter results are given of the assessment of the models that were developed in the previous chapter. First, the outcomes per method are provided and evaluated, after which all model performances will be compared. The chapter finishes with a sensitivity analysis.

8.2 Naïve models

The naïve models (see 7.3) are fed with Origin data and the outcomes (Result data) are compared with the Target data. Origin, Result and Target data can be chronologically ordered (element by element) and thus form vectors. The Error vector is constructed by subtraction of the Result vector with the Target vector on an element by element basis. The element values of the resulting Error vector are multiplied by a factor of 1.25 for normalisation purposes. Every element that is not equal to '0' is considered an error. Elements of the Error vector with value '+1' are the model's translation of 'congestion', when in reality no congestion occurred, so the model gave a *false alarm*. Elements of the modified error vector with value '-1' are the model's translation of 'no congestion', when in reality congestion occurred; these outputs are defined as *error*. The assessment can be carried out for any number of minutes keeping in mind the restriction that the prediction horizon should not exceed the shortest 'no congestion' period after 6:00 hours and before 11:00 hours in the morning. The assessment results of the naïve method for the two peak periods and the two locations are displayed in figures 8.1-4.

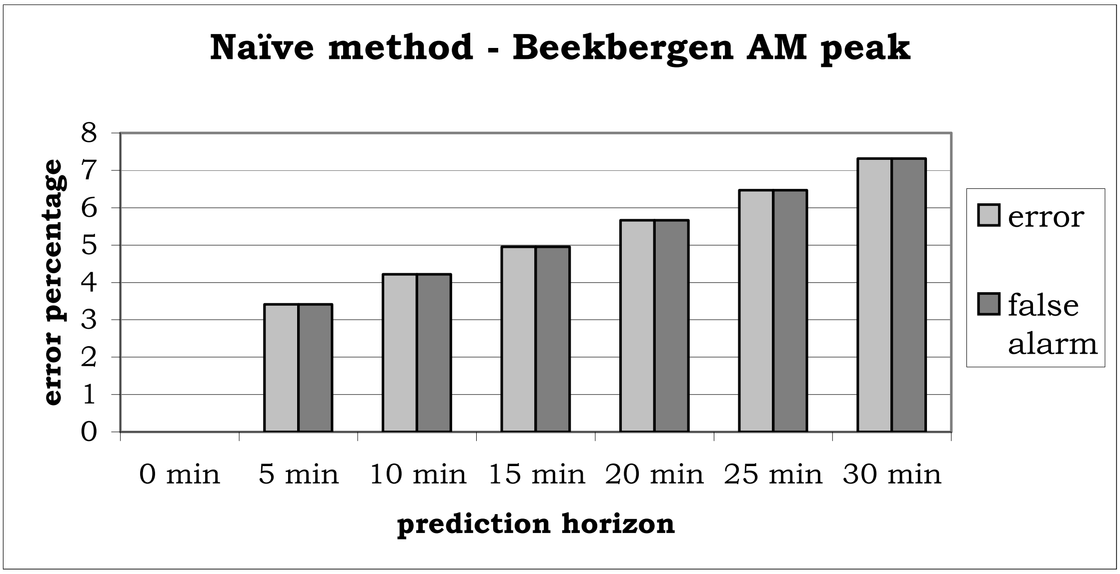

Figure 8.1: Results of the naïve method for the Beekbergen AM peak period.

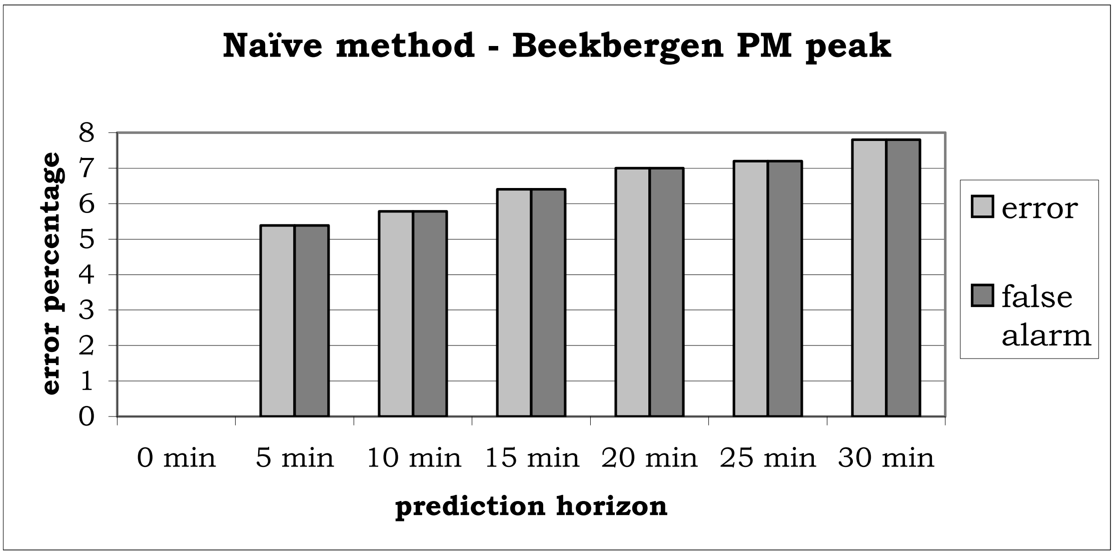

Figure 8.2: Results of the naïve method for the Beekbergen PM peak period.

By definition, the results produced by the naïve models for 'error' and 'false alarm' score the same value. Figure 8.1 and figure 8.2 show that as the prediction horizon increases the error percentage also increases, although the error increase during the morning peak period is more regular than the error increase during the evening peak period. A similar increase in error with time occurs in the Hoevelaken AM peak period (figure 8.3).

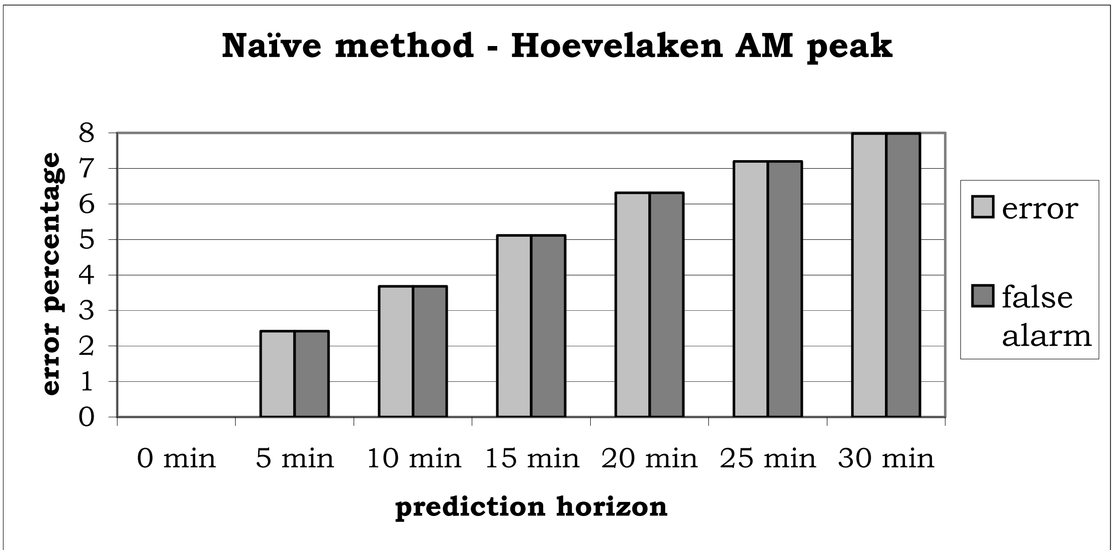

Figure 8.3: Results of the naïve method for the Hoevelaken AM peak period.

However, in the Hoevelaken PM peak period (figure 8.4), the error percentage does not increase linearly with time. For instance, the error percentage of the 15 minutes prediction horizon is lower than the error percentage of the 10 minutes prediction horizon. The same holds for the 25 and the 20 minutes prediction horizon, respectively.

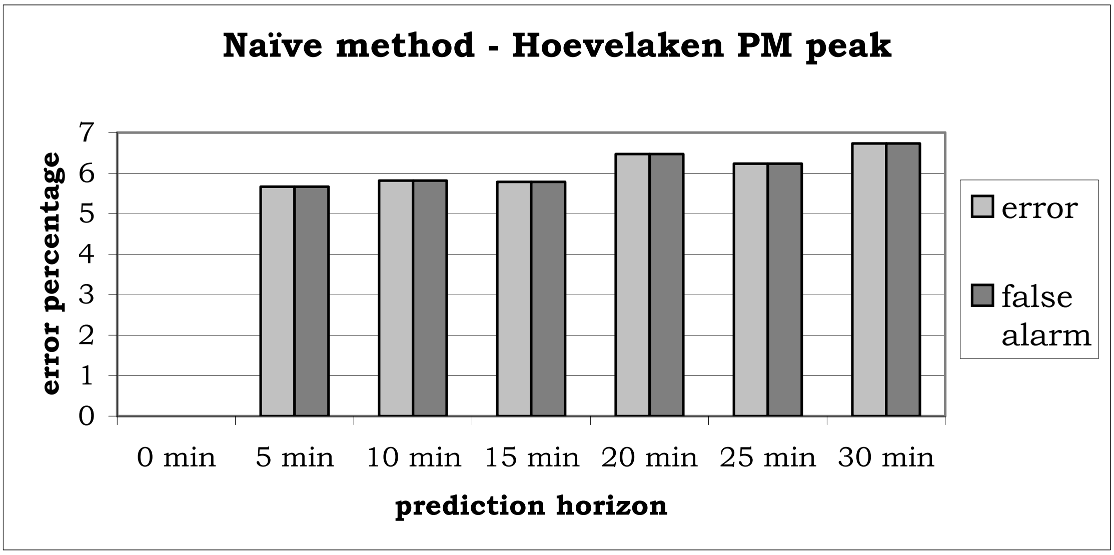

Figure 8.4: Results of the naïve method for the Hoevelaken PM peak period.

The reason for this counter-intuitive phenomenon can be found in the target data set. Closer inspection of the Hoevelaken PM peak period (appendix I) shows that the bottleneck detector reports congestion for a short period of time (typically 2-4 minutes) followed by an intermediate period of several minutes before the next small congestion period is reported. Since the error definition is not event related, this ‘stop-and-go’ traffic can easily cause the naïve model to produce results that coincide with target values of a small congestion period that took place one or two intermediate period(s) later. If the intermediate period is more often about fifteen minutes than ten minutes, the results of the naïve method for the 15 minutes prediction horizon will be better than those of the 10 minutes prediction horizon.

8.3 MLR models

The MLR models were developed as described in 7.4 and were in turn calibrated with 3 data sub-sets and evaluated with the remaining data sub-set according to the procedure that was described in chapter 7. The evaluation results are given for seven prediction horizons of the morning and evening peak period of the Beekbergen and Hoevelaken location. The mean of the results of the sub-sets was taken for ‘false alarm’, i.e. whenever the model predicted that the bottleneck detector should suffer from a congested traffic stream when, in fact, it did not. Additionally, the mean of the results of the sub-sets was taken for ‘error’, i.e. whenever the model predicted that the bottleneck detector should report a congestion free traffic stream, when, in fact, it did suffer from congestion.

The results displayed in figures 8.5 are the mean error and mean false alarm percentages as they were produced by the MLR method for the Beekbergen location during the AM peak period.

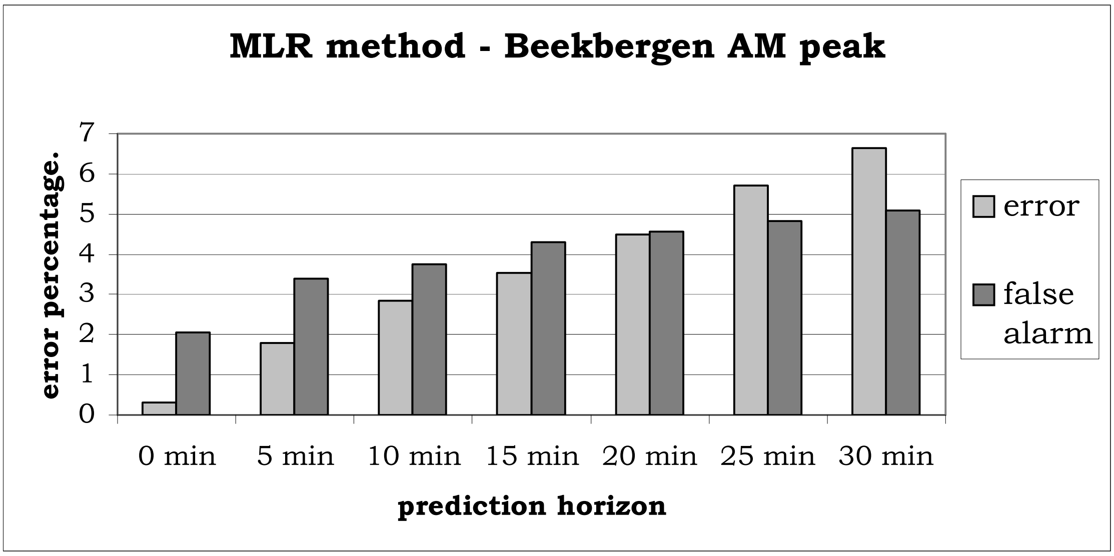

Figure 8.5: Results of the MLR method for the Beekbergen AM peak period.

Similar to the results of the naïve method, the error percentages of the AM peak period increase as the prediction period increases. After starting of with a low percentage, the error percentage increases faster than the false alarm percentage that started with a higher initial percentage.

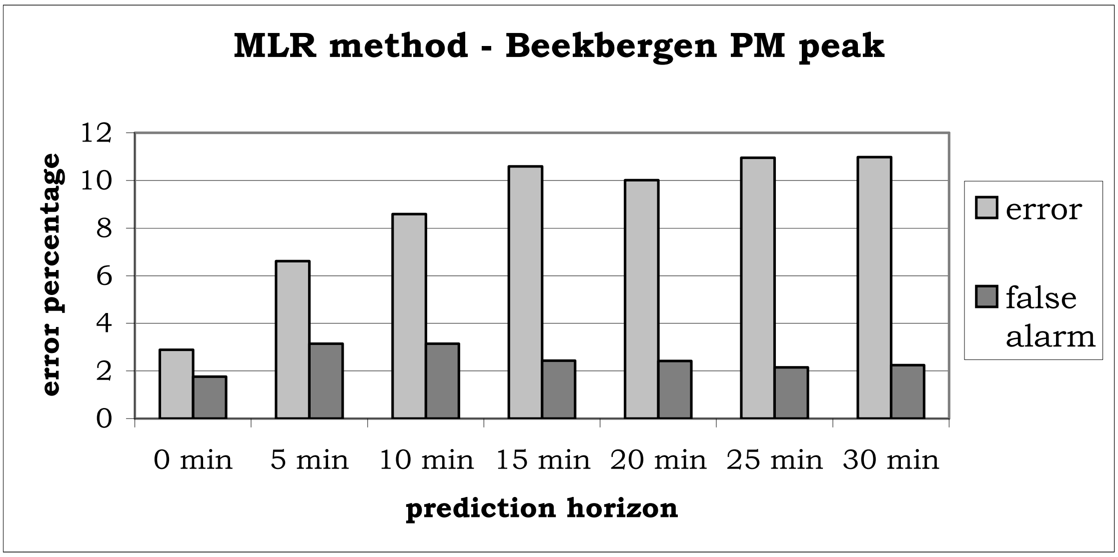

Figure 8.6: Results of the MLR method for the Beekbergen PM peak period.

The results of the Beekbergen PM peak period are different (figure 8.6). Error percentages increase with time up to 15 minutes, then level of.

There is an initial increase followed by a decrease of the false alarm percentage during the 0 – 15 minutes prediction horizon increase.

The results for the Hoevelaken AM peak are displayed in figure 8.7.

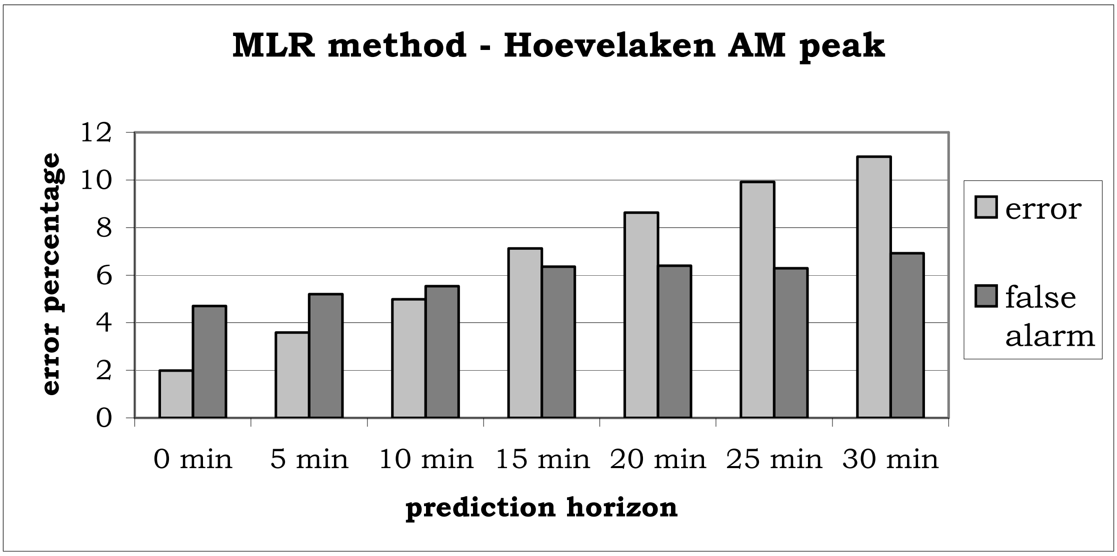

Figure 8.7: Results of the MLR method for the Hoevelaken AM peak period.

During the peak period, the error percentage increases almost linearly with the prediction horizon. However, the false alarm percentage seems to level off when the prediction horizon reaches 15 minutes and above.

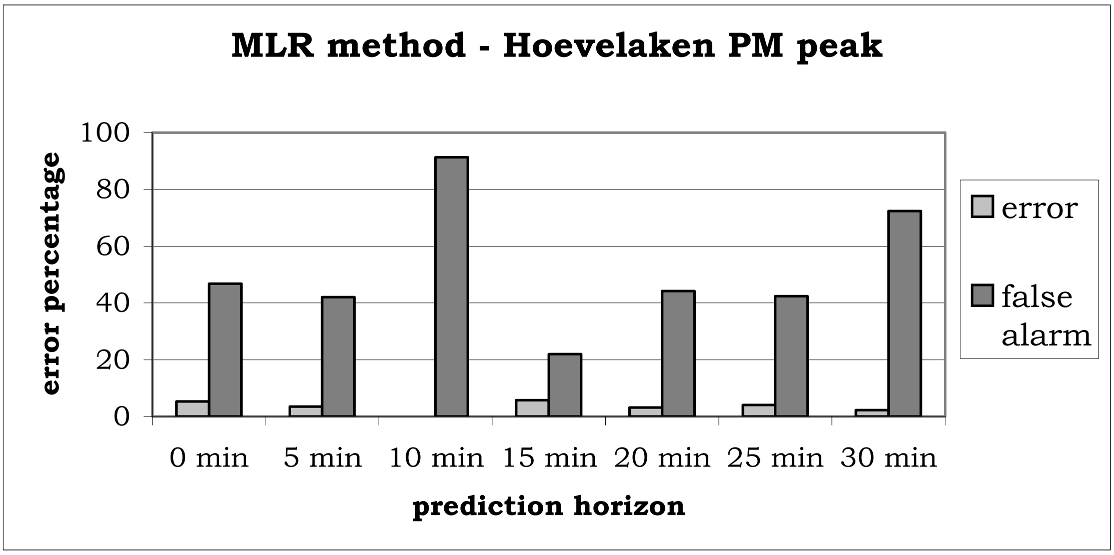

Figure 8.8: Results of the MLR method for the Hoevelaken PM peak period.

During the PM peak period (figure 8.8) there are unusual high false alarm percentages. This is due to the fact that during the modelling process, data are arranged to form matrices and that during the calculation of the inverse of these large matrices (see section 3.3) may result in the creation of singular points (see Jänich, 1990). The creation of singularities is caused by input variables that are not mutually independent, non-linear relationships between input and output variables, and/or residuals (the errors between the real observed value and the MLR value) that have no normal distribution or are uncorrelated with the input variables (these are theoretical restrictions on the use of MLR). This is also what has happened during the model development of the Hoevelaken PM peak period models and makes the resulting models unfit to be used as congestion prediction models.

8.4 ARMA models

ARMA models were developed as described in 7.5. Similar to the procedure described in section 8.3 to estimate the performance of the MLR models, the ARMA models were also in turn calibrated with 3 data sub-sets and evaluated with the remaining data sub-set. The evaluation results are given for the same seven prediction horizons of the morning and evening peak period of the Beekbergen and Hoevelaken locations and the results were estimated similarly. Model performances are carried out by means of error measurements that are identical to the error measurement as described in 8.3, i.e. the mean of 'false alarm' (prediction of congested traffic, when in reality the traffic is free of congestion) and the mean of 'error' (prediction of a congestion free traffic stream, when in reality congestion occurs).

Figure 8.9 displays the results of the ARMA models that were fed with input data acquired during AM peak periods at the Beekbergen location.

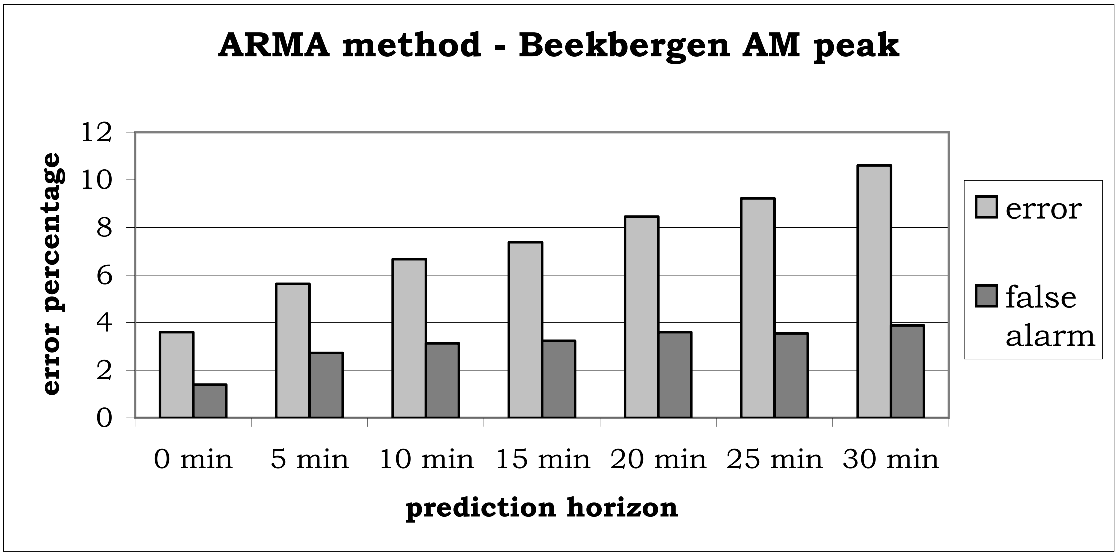

Figure 8.9: Results of the ARMA method for the Beekbergen AM peak period.

The error percentage gives a linear increasing trend as the prediction horizon increases. The false alarm varies between 3 and 4 % at 10 minutes and beyond.

The evening peak period shows different trends (figure 8.10). There was an increase in the error percentage when the prediction horizon expands between zero and 5 minutes, followed by a linear increase in error between 5 and 20 minutes after which the error percentage levels off. The pattern for false alarm is identical to the results of the MLR method.

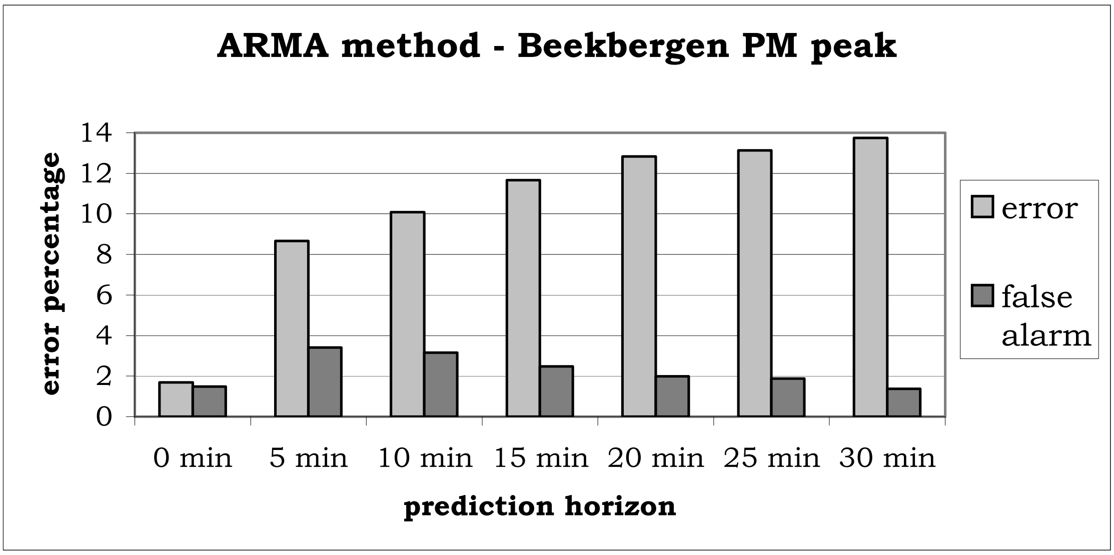

Figure 8.10: Results of the ARMA method for the Beekbergen PM peak period.

The results of the ARMA models for the Hoevelaken location during the AM peak are displayed in figure 8.11.

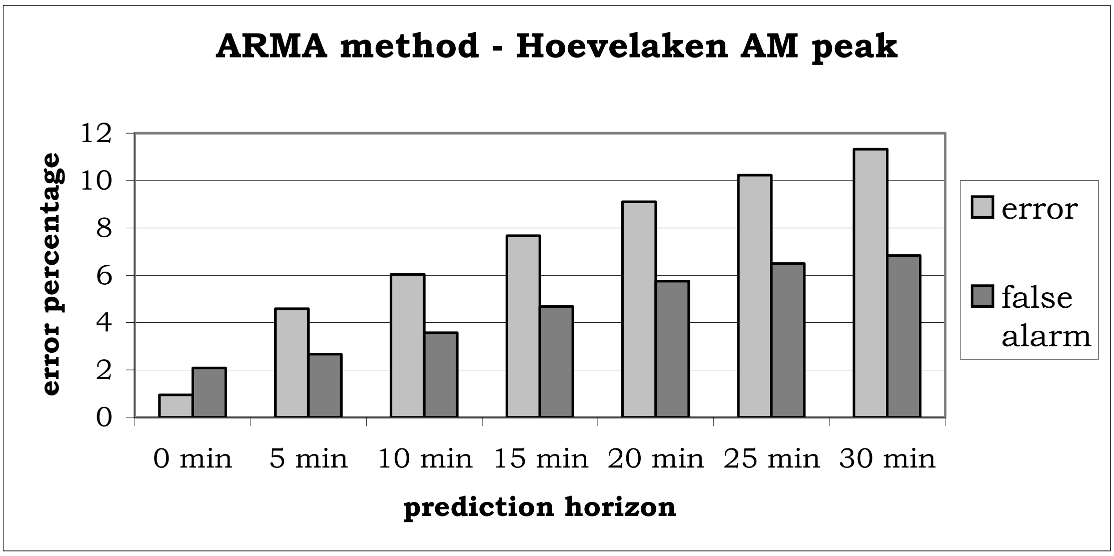

Figure 8.11: Results of the ARMA method for the Hoevelaken AM peak period.

The results depicted in figure 8.11 show that the error percentage as well as the false alarm percentage are almost linear increasing with an increasing prediction horizon. However, the rate of increase with time is larger for the error percentage than for the false alarm percentage. Comparing these results with those of the MLR models, it is noteworthy that, although the error percentage results are similar, the false alarm percentages are substantially lower for the ARMA models, especially in the prediction horizon region from 0 – 20 minutes.

The results for the evening peak period of the ARMA models at the Hoevelaken location are shown in figure 8.12.

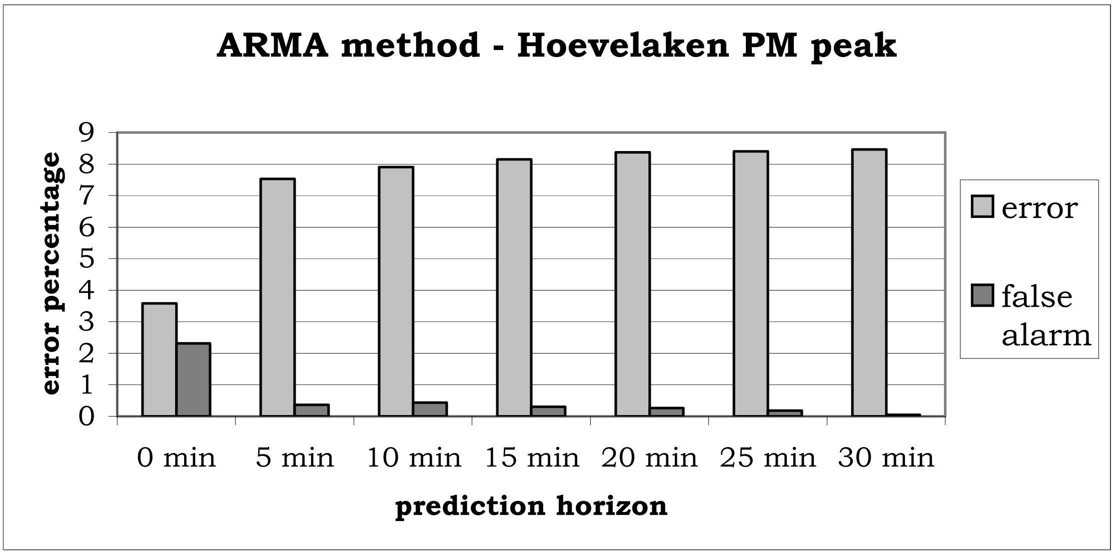

Figure 8.12: Results of the ARMA method for the Hoevelaken PM peak period.

Again, just as for the MLR models, the ARMA models produce the worst results for the Hoevelaken location during the evening peak period, certainly for the relatively short prediction horizon periods (0 – 15 minutes). The error percentage levels off after the 5-minutes prediction horizon and, interestingly, the false alarm percentage drops to below one percent after the prediction horizon is 5 minutes or more.

Is there a logical explanation for this observed phenomenon? On examination of the source data for Beekbergen location during the evening period it can be shown that the target data detector reports low percentages of congested traffic. In fact, whenever the traffic state is reported as congested by the target detector, traffic suffers from stop-and-go traffic congestion for the majority of the events. Additionally, the time that the target detector reports congestion is equal to 8.5 percent of the total evening peak period under research.

The reason for the ARMA models to produce an error percentage of almost 8.5 percent can be found in the output of the models: it shows an almost constant 'no congestion'. This causes error percentages of nearly 8.5 percent and false alarm percentages of approximately 0 percent.

How were the ARMA models selected? The models that produced the lowest mean error (a combination of error and false alarm) during the test and validation phase, see chapter 7, were selected. Since the reported congestion in most of the cases can be classified as stop-and-go congestion (meaning that the state of traffic changes from 'congestion' to 'no congestion' within minutes – it "flip-flops") it is very difficult for the models to actually predict this kind of congestion when the prediction horizon is e.g. 20 minutes. Therefore, during the validation phase the best results are given by models that for most of the time report 'no congestion' (since only 8.5 percent of the time congestion is actually present) and only during longer periods of congestion report 'congestion'.

8.5 MLF models

MLF models were developed as described in 7.6. Similar to the procedure described in paragraphs 8.3 to estimate the performance of the MLR models, the MLF models were also in turn calibrated with 3 data sub-sets and evaluated with the remaining data sub-set. The evaluation results are given for the same seven prediction horizons of the morning and evening peak period of the Beekbergen and Hoevelaken location and the model's performances are measured following the same procedure for 'error' and 'false alarm'.

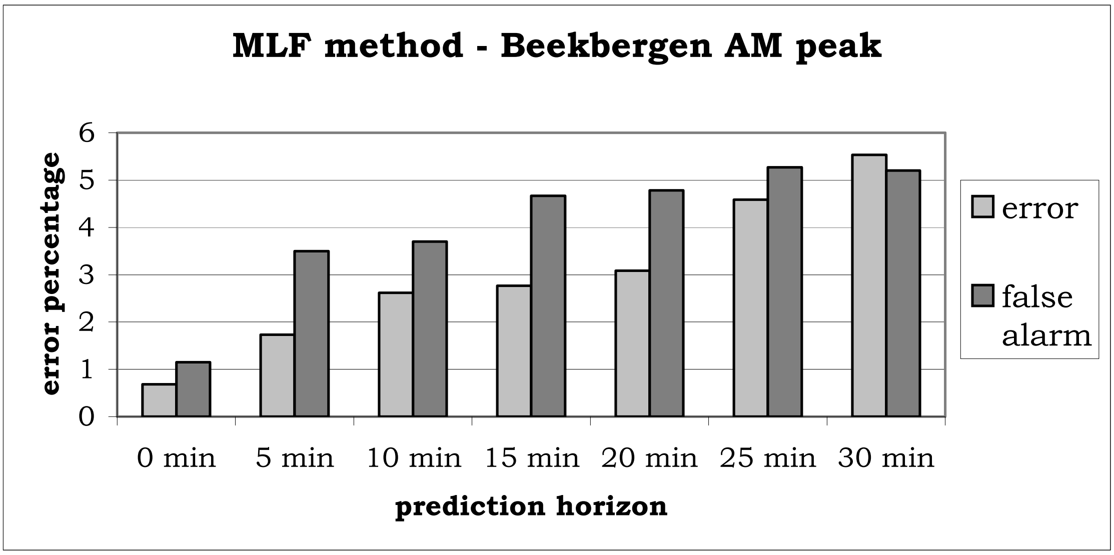

Figure 8.13: Results of the MLF method for the Beekbergen AM peak period.

Figure 8.13 shows the results of the MLF models for the Beekbergen morning peak period. Although the false alarm percentages are slightly higher than for the ARMA models, the error percentages produced by the MLF models are substantially lower than those produced by the ARMA models.

The results of the MLF models for the Beekbergen evening peak period (figure 8.14) show that the development of the false alarm percentage is intuitive more logical than the patterns produced by the MLR and ARMA models (see figures 8.6 and 8.10, respectively). The error percentages are lower than those of the MLR and ARMA models, however, the false alarm percentages are higher.

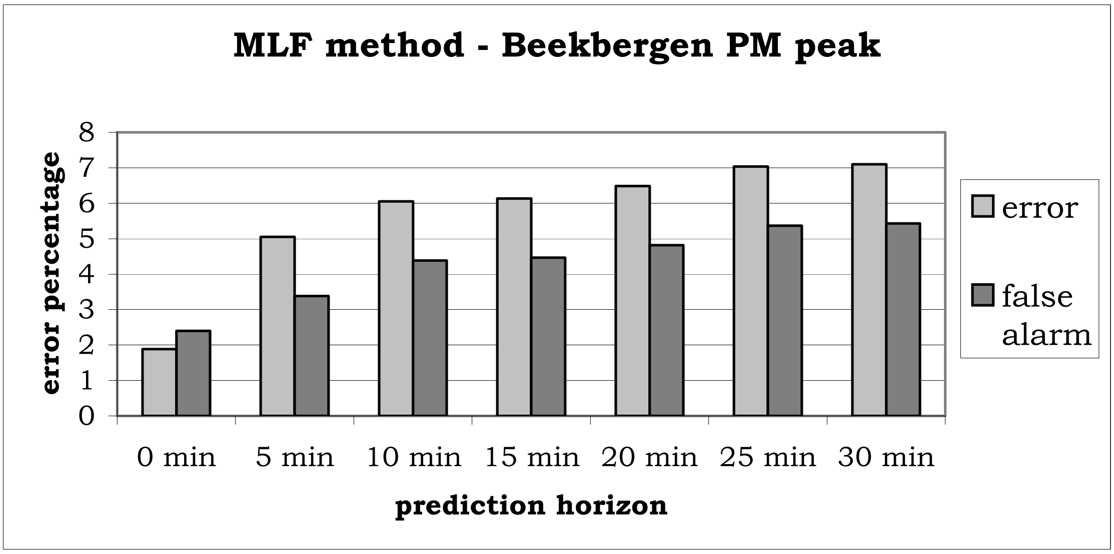

Figure 8.14: Results of the MLF method for the Beekbergen PM peak period.

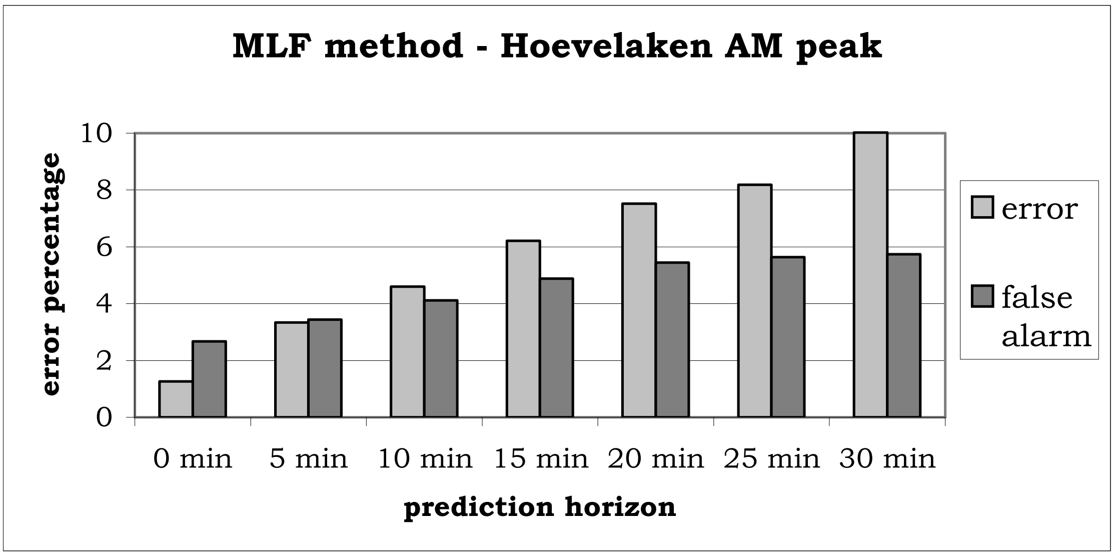

Figure 8.15: Results of the MLF method for the Hoevelaken AM peak period.

Again, figure 8.15 shows a linear tendency for increasing error percentage as the prediction horizon increases. The false alarm percentage also increases linearly until the prediction horizon reaches 20 minutes; after which it levels off.

The results of the MLF models for the Hoevelaken evening peak period (figure 8.16) are similar to the results obtained by the ARMA models (figure 8.12). Hence, the explanation is also identical to the one given at 8.5.

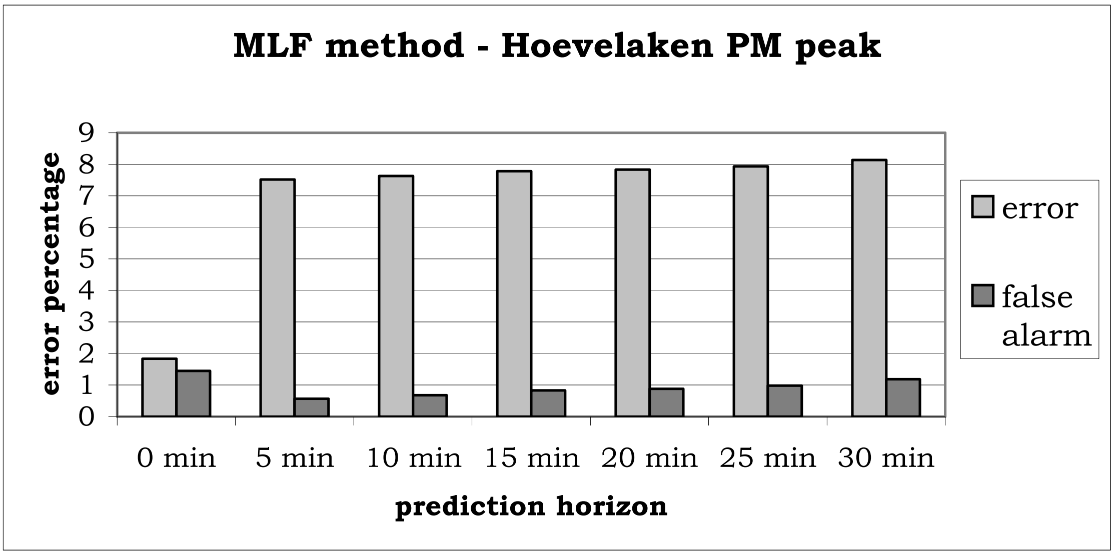

Figure 8.16: Results of the MLF method for the Hoevelaken PM peak period.

8.6 RBF models

RBF models were developed as described in 7.6. Similar to the procedure described in paragraph 8.3 to estimate the performance of the MLR models, the RBF models were also in turn calibrated with 3 data sub-sets and evaluated with the remaining data sub-set. The evaluation results are given for the same seven prediction horizons of the morning and evening peak period of the Beekbergen and Hoevelaken location and the model's performances are measured following the same procedure for 'error' and 'false alarm'.

Figure 8.17 displays the results of the RBF models for the Beekbergen morning peak period. Although the false alarm percentages are slightly higher than those obtained with the ARMA models, the linearly increasing error percentages produced by the RBF models are substantially lower than those produced by the ARMA models. However, the error percentages are slightly higher than those obtained with the MLF models.

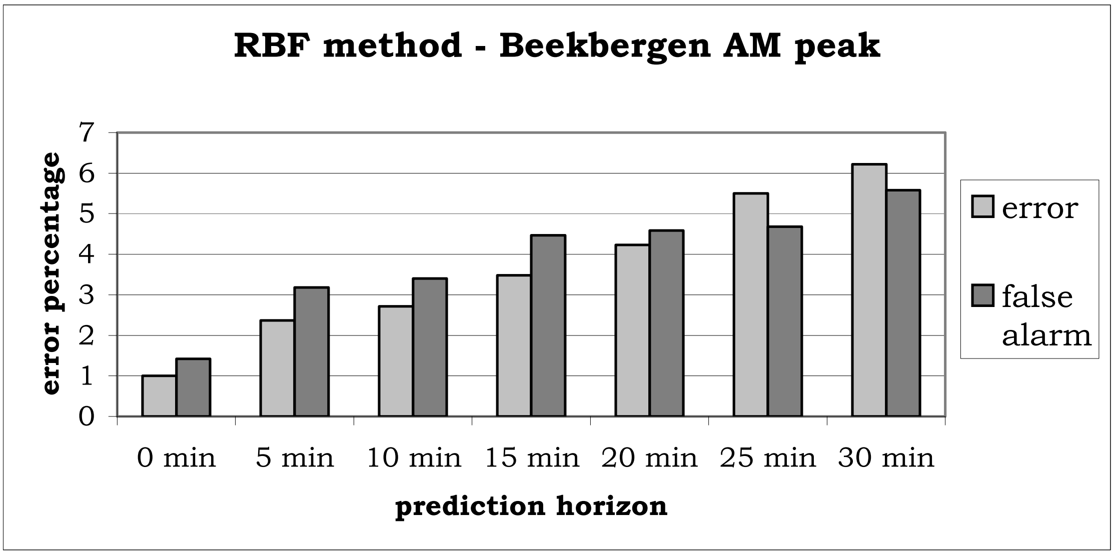

Figure 8.17: Results of the RBF method for the Beekbergen AM peak period.

The evening peak results for the Beekbergen location obtained by the RBF models (figure 8.18) show a different pattern from those produced by the MLF models (figure 8.14). The false alarm percentages of the RBF models are lower, however, the error percentages are higher. The error percentages are stable when the prediction horizon reaches 10 minutes and longer.

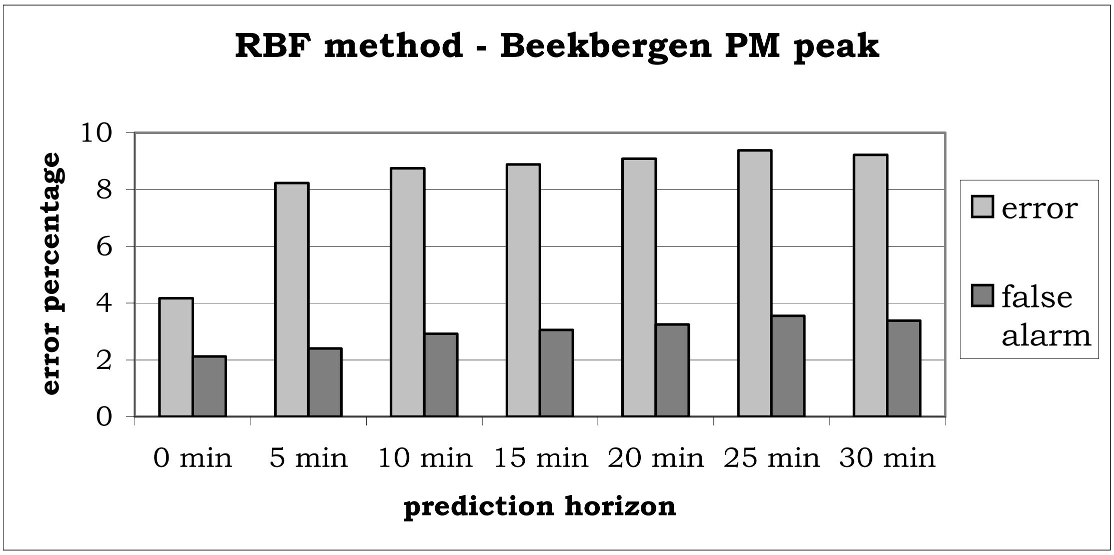

Figure 8.18: Results of the RBF method for the Beekbergen PM peak period.

The results of the assessment on the RBF models for the Hoevelaken morning peak are given in figure 8.19. The error percentage is linearly increasing with the prediction horizon period. The false alarm percentages increase as the prediction horizon gets longer until it reaches 10 minutes, after which the false alarm percentages drop.

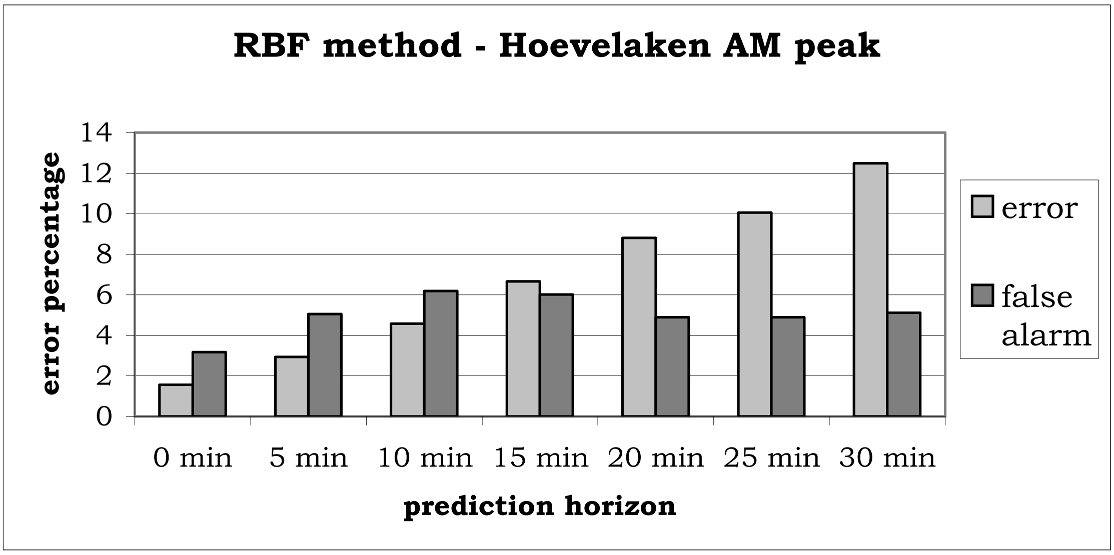

Figure 8.19: Results of the RBF method for the Hoevelaken AM peak period.

The results of the RBF models for the Hoevelaken evening peak period are also similar to the results obtained by the ARMA and the MLF models. Actually, the results displayed in figure 8.20 show that the RBF models that gave the best results were those that gave 'no congestion' as output all the time for all prediction horizons of 5 minutes or longer, with the same explanation as the one given in 8.5. The output 'no congestion' clearly produced the best results for all but one prediction horizon of the test set and therefore this has been transposed to the RBF models with a prediction horizon of 5 minutes and higher.

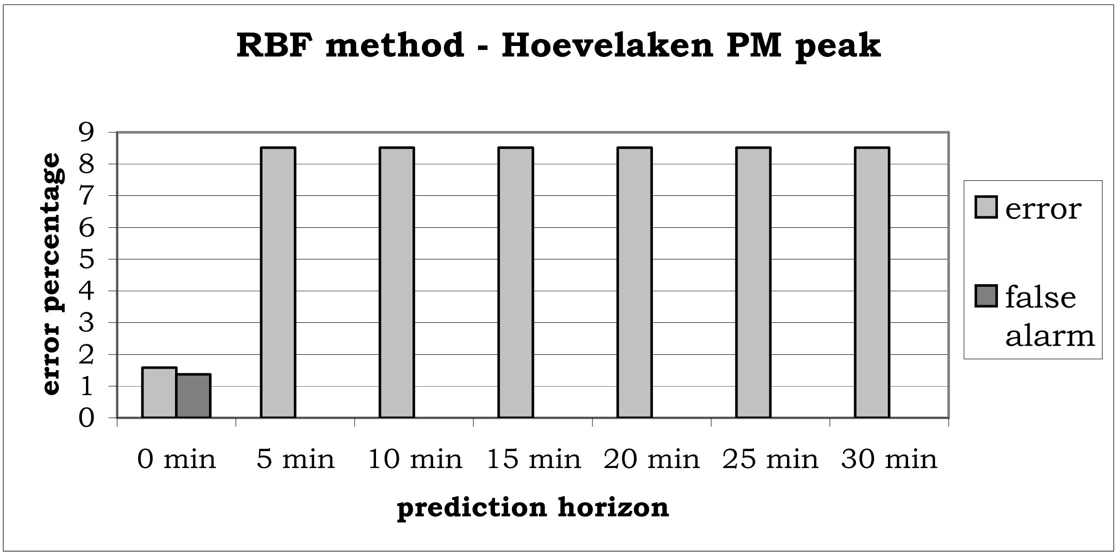

Figure 8.20: Results of the RBF method for the Hoevelaken PM peak period.

8.7 Elman model

The model development of the Elman models is described in section 7.7. Similar to the procedure described in paragraph 8.3 to estimate the performance of the MLR models, the Elman models were also in turn calibrated with 3 data sub-sets and evaluated with the remaining data sub-set. The evaluation results are given for the same seven prediction horizons of the morning and evening peak period of the Beekbergen and Hoevelaken location and the model's performances are measured following the same procedure for 'error' and 'false alarm'.

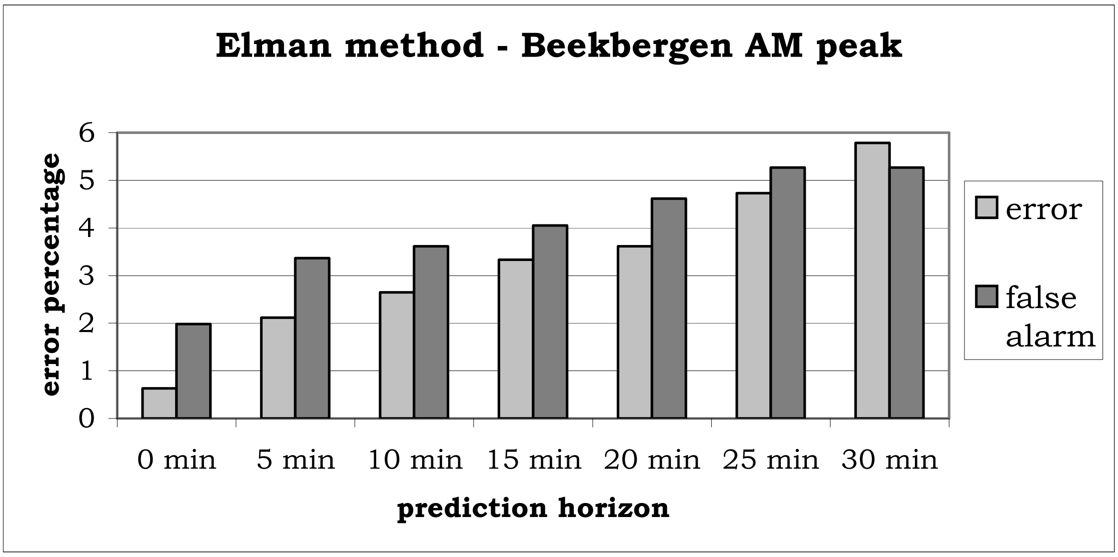

Figure 8.21: Results of the Elman method for the Beekbergen AM peak period

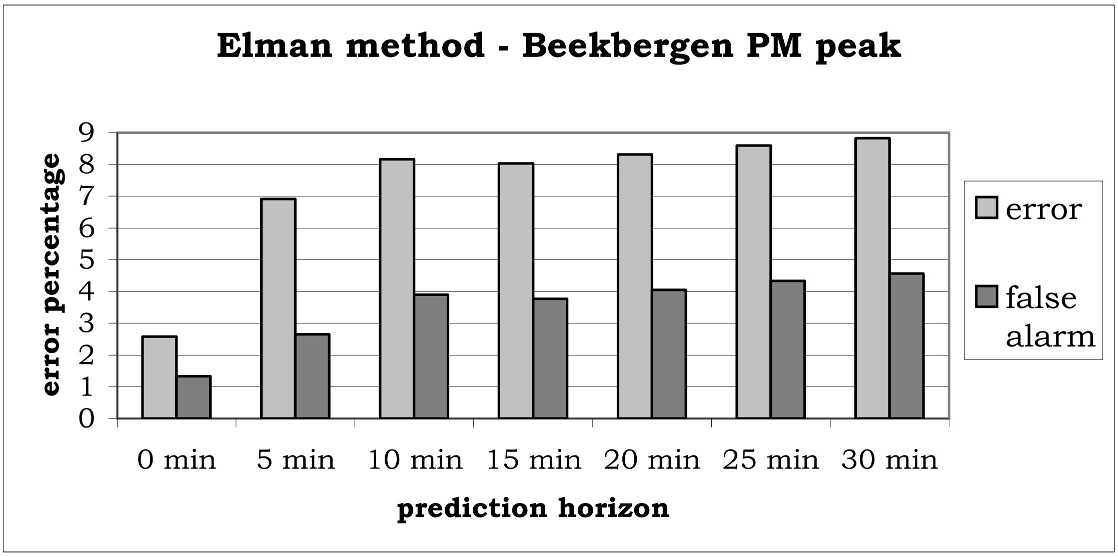

Figure 8.22: Results of the Elman method for the Beekbergen PM peak period.

Figure 8.21 shows the results of the Elman models for the Beekbergen morning peak period. The false alarm percentages are slightly higher and the error percentages are slightly lower then the percentages produced by the MLF models, however, adding both percentages gives almost identical percentages for MLF and Elman models.

Figure 8.22 presents the output of the Elman models for the Beekbergen evening peak period. Although the false alarm percentages for the Elman models are lower than those of the MLF models, the error percentages are that much higher than those of the MLF models so that the combination of both percentages results in better outcomes for the MLF models.

Figure 8.23 displays the results of the Elman models produced during the morning peak at location Hoevelaken. The trend that the false alarm percentages are lower than the error percentages (except for the 0-minute prediction horizon) is quite similar to the trend of the MLF models for the Hoevelaken morning peak. Also, the combined percentages are close to those produced by the MLF models. The most pronounced difference between the output of the Elman and the MLF models concerns the difference between the false alarm percentages and the error percentages for prediction horizons of 20 minutes and longer; the difference between false alarm percentages and error percentages is more clearly visible for the MLF model outputs (figure 8.15).

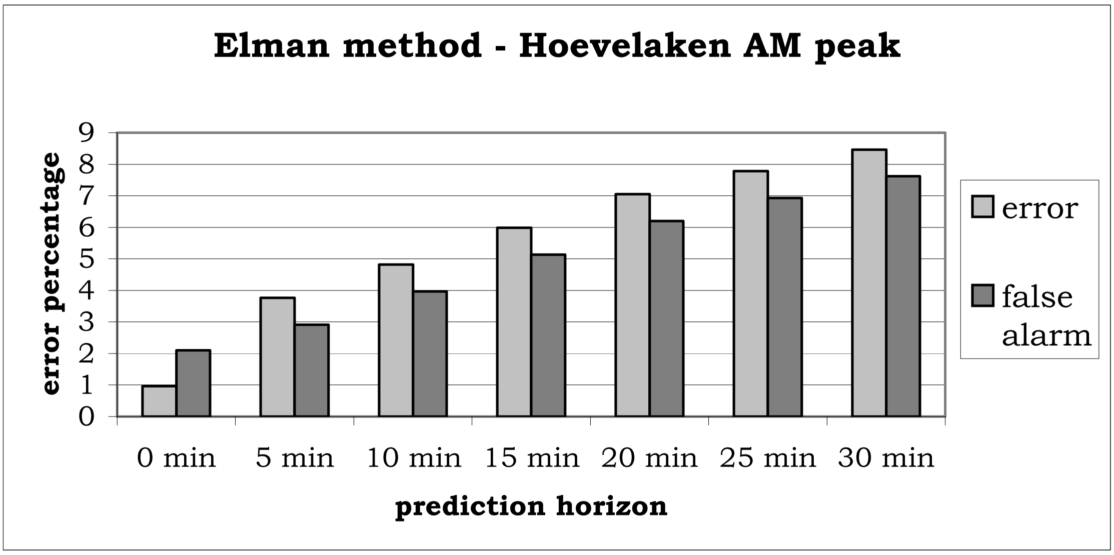

Figure 8.23: Results of the Elman method for the Hoevelaken AM peak period.

Figure 8.24 holds the results of the Elman models for the Hoevelaken evening peak period. These seem like a replica of the MLF model outcomes (figure 8.16) and are also similar to the results obtained by the ARMA models. The explanation is, once again, also similar to the one given in 8.5.

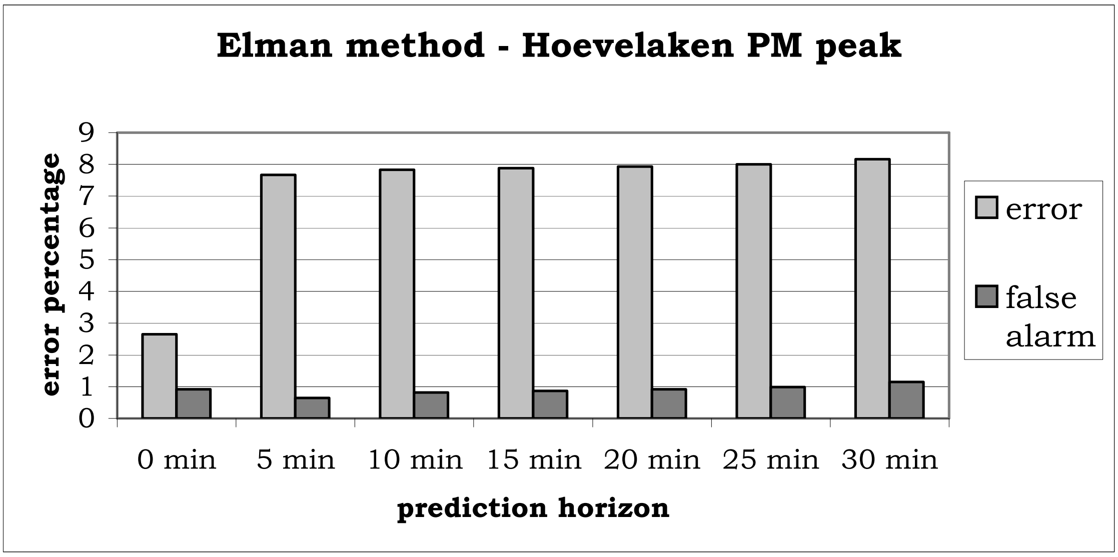

Figure 8.24: Results of the Elman method for the Hoevelaken PM peak period.

8.8 SOM models

Similar to the procedure described in paragraph 8.3 to estimate the performance of the MLR models, the SOM models were also in turn calibrated with 3 data sub-sets and evaluated with the remaining data sub-set. The evaluation results are given for the same seven prediction horizons of the morning and evening peak period of the Beekbergen and Hoevelaken location and the model's performances are measured following the same procedure for 'error' and 'false alarm'.

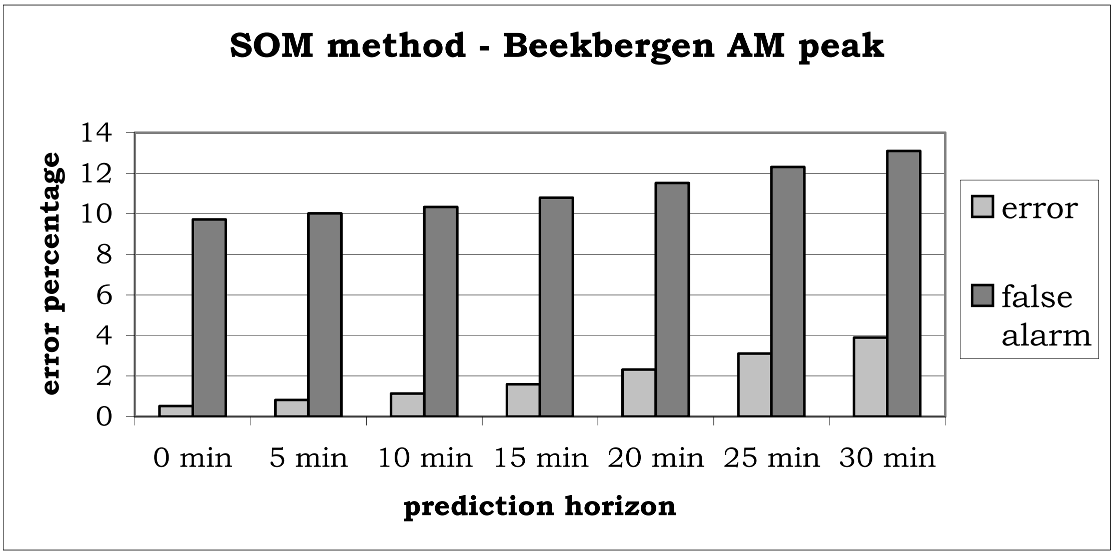

Figure 8.25: Results of the SOM method for the Beekbergen AM peak period.

The results of the SOM models for the Beekbergen AM peak period are displayed in figure 8.25. The false alarm percentages are high and slightly increasing, whereas the error percentages are lower and slightly increasing. When adding both percentages the resulting outcomes reveal that SOM models produce by far the worst predictions.

The results of the SOM models for the Beekbergen AM peak are surpassed by the percentages produced by the Beekbergen PM peak models (figure 8.26). The percentages show that SOM models developed as they are make a bad choice as a congestion prediction tool.

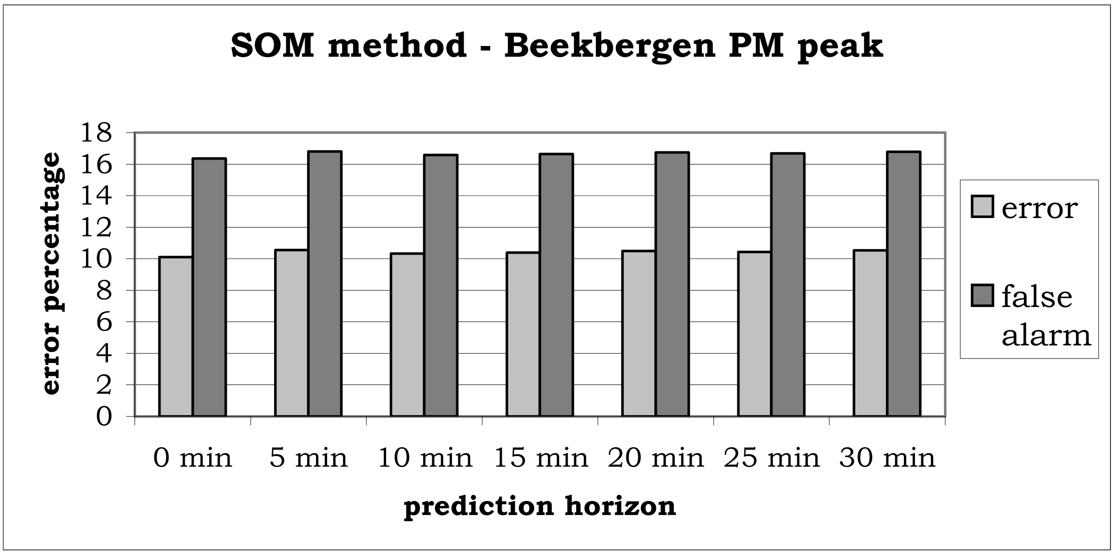

Figure 8.26: Results of the SOM method for the Beekbergen PM peak period.

Figure 8.27 confirms this conclusion. The results for the Hoevelaken morning peak are also very poor.

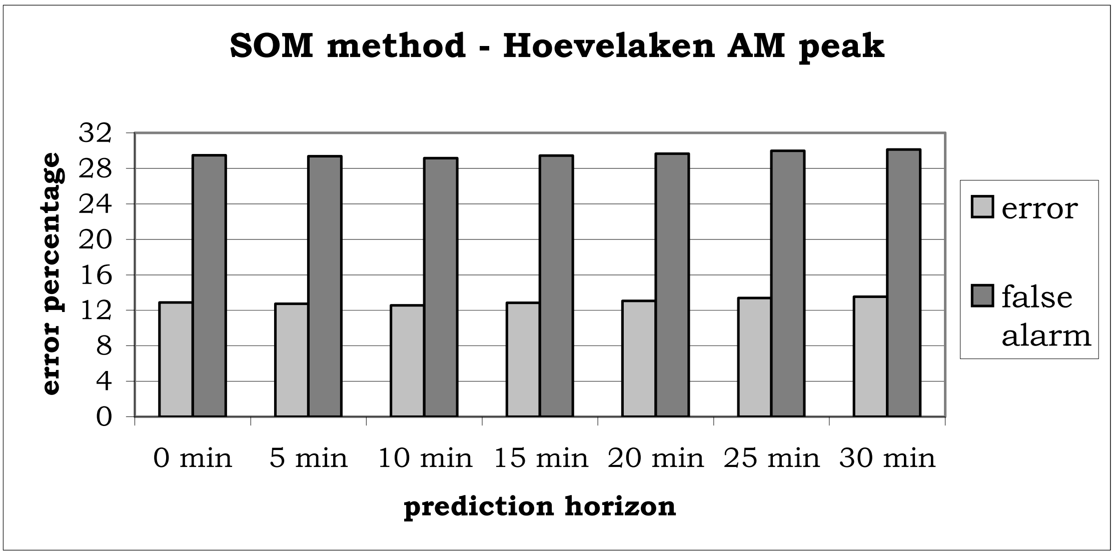

Figure 8.27: Results of the SOM method for the Hoevelaken AM peak period.

Figure 8.28 shows the results of the SOM models for the Hoevelaken evening peak. The results are even worse than if the models produce 'no congestion' all the time (as the RBF models did, see 8.6).

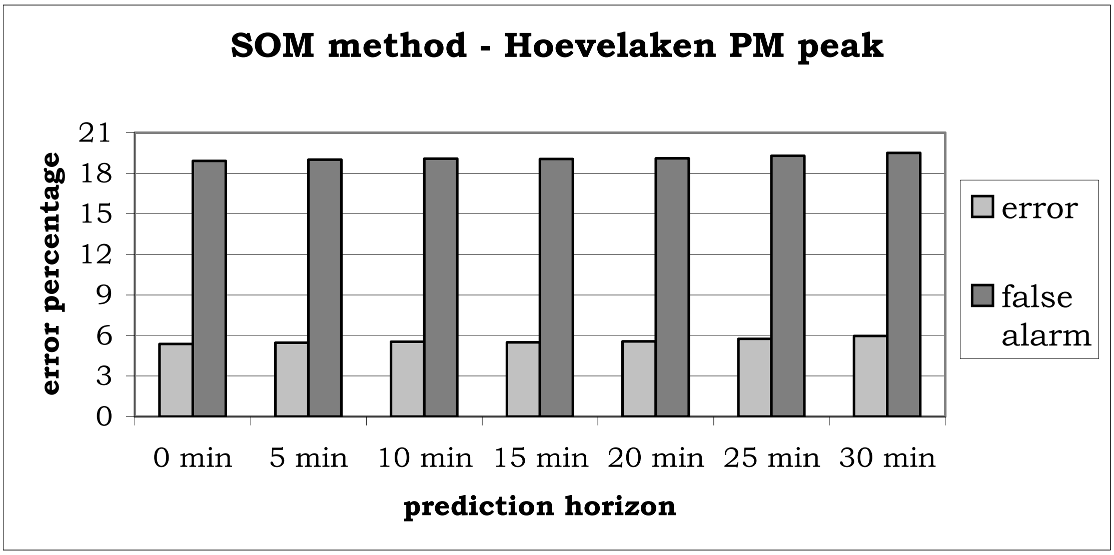

Figure 8.28: Results of the SOM method for the Hoevelaken PM peak period.

8.9 FL models

Similar to the procedure described in paragraph 8.3 to estimate the performance of the MLR models, the Fuzzy Logic models were also in turn calibrated with 3 data sub-sets and evaluated with the remaining data sub-set.

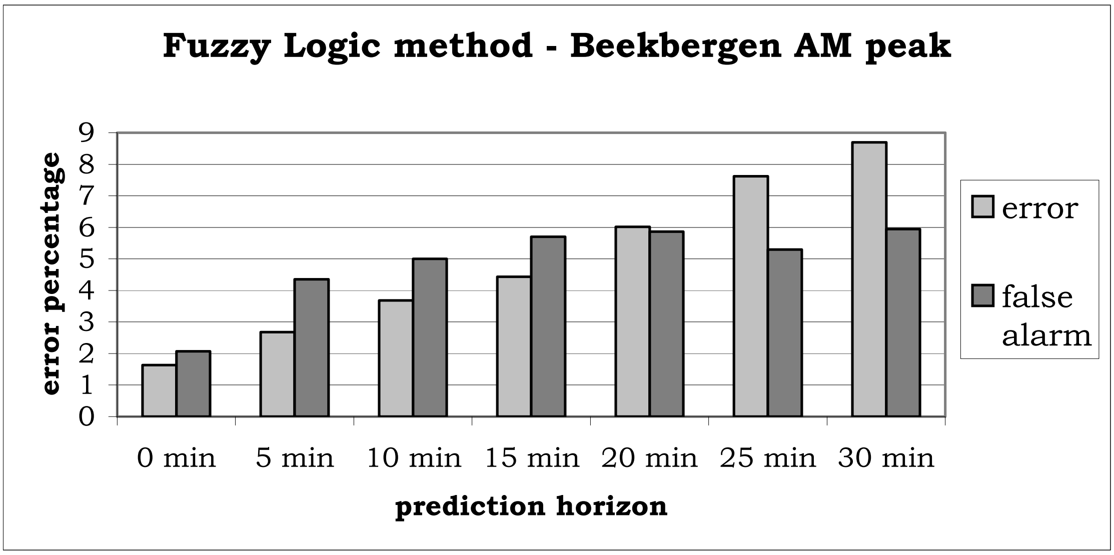

Figure 8.29: Results of the FL method for the Beekbergen AM peak period.

The evaluation results are given for the same seven prediction horizons of the morning and evening peak period of the Beekbergen and Hoevelaken location and the model's performances are measured following the same procedure for 'error' and 'false alarm'.

Figure 8.29 shows the results of the Beekbergen morning peak and figure 8.30 displays the results of the evening peak. Both figures show that for the Beekbergen location, the fuzzy logic models are outperformed by the supervised neural network models. The FL models produce results that resemble those of the naïve models and the time series models.

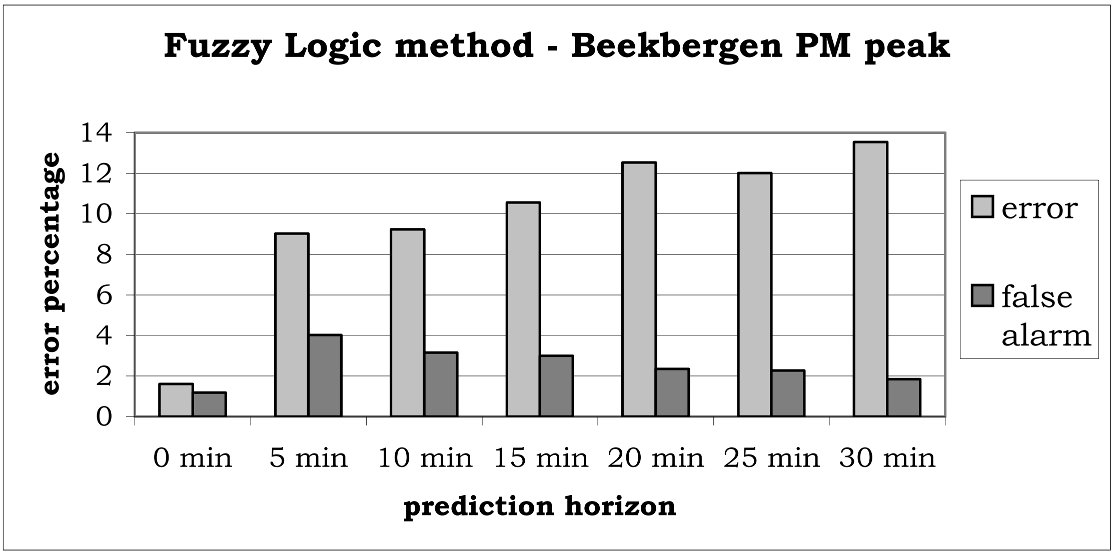

Figure 8.30: Results of the FL method for the Beekbergen PM peak period.

Figure 8.31 shows the results of the Hoevelaken morning peak period.

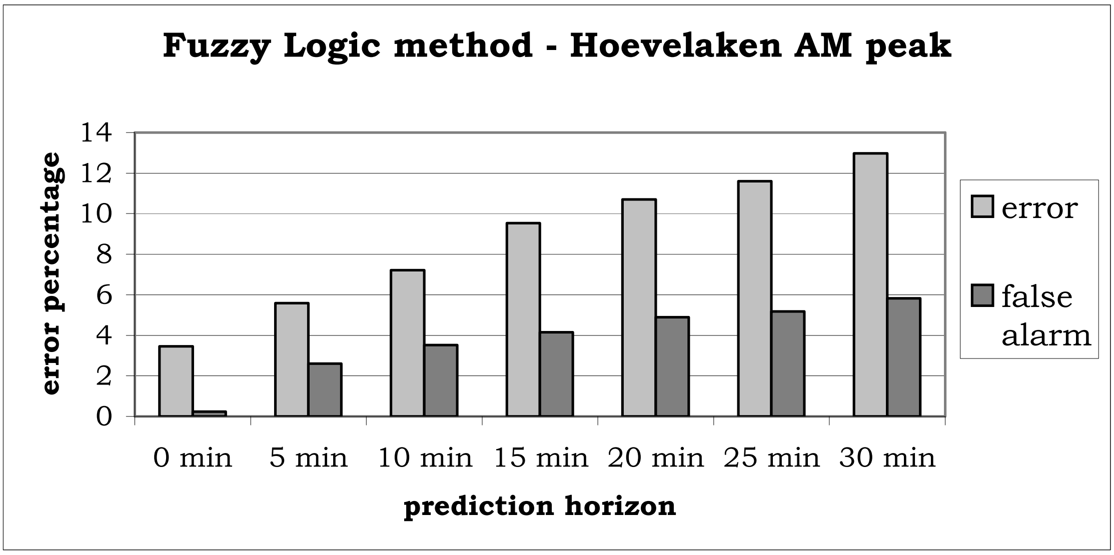

Figure 8.31: Results of the FL method for the Hoevelaken AM peak period.

The combined results for error and false alarm of the FL models are almost identical to those produced by the MLR models (figure 8.7). The difference between both model outputs is the division between error percentage and false alarm percentage. The FL models have a significant lower false alarm percentage than the MLR models, which, in turn have a significant lower error percentage than the FL models.

Figure 8.32 depicts the Hoevelaken evening peak period results of the FL models. The results are, again, very similar to those of the ARMA, MLF and Elman model outcomes (figures 8.12, 8.16 and 8.24). The explanation is given in section 8.5.

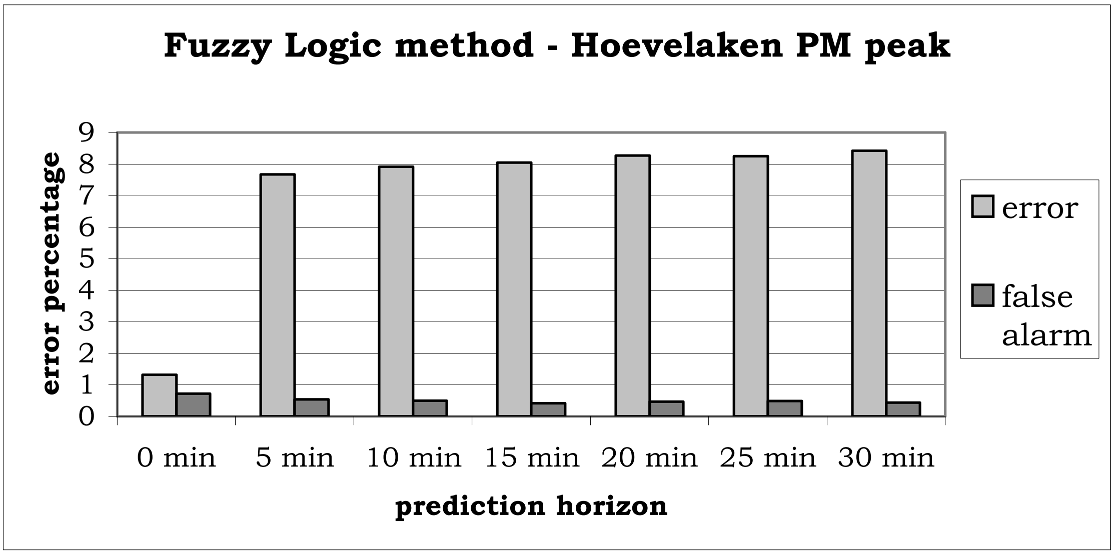

Figure 8.32: Results of the FL method for the Hoevelaken PM peak period.

8.10 Comparing the model performances

This section reports on the results of all models per location and per peak period. The results for all (eight) models for six prediction horizon periods are given (the 0-minute prediction horizon is left out due to its impractical value – it was only included in the previous sections of this chapter to get an impression of the initial mismatch between model output and the target data). The combined error percentages are built up of error percentage plus false alarm percentage adding to the total error percentage of time that the model did not correctly predict how the target detector reports on the congestion state of the traffic. The results are then related to the location of the target detector and the location of other detectors, the percentage that the target detector did report congestion and the kind of congestion that was reported.

8.10.1 Beekbergen AM peak period

Figure 8.33 shows the combined error percentages produced by all Beekberger models during the morning peak for each prediction horizon.

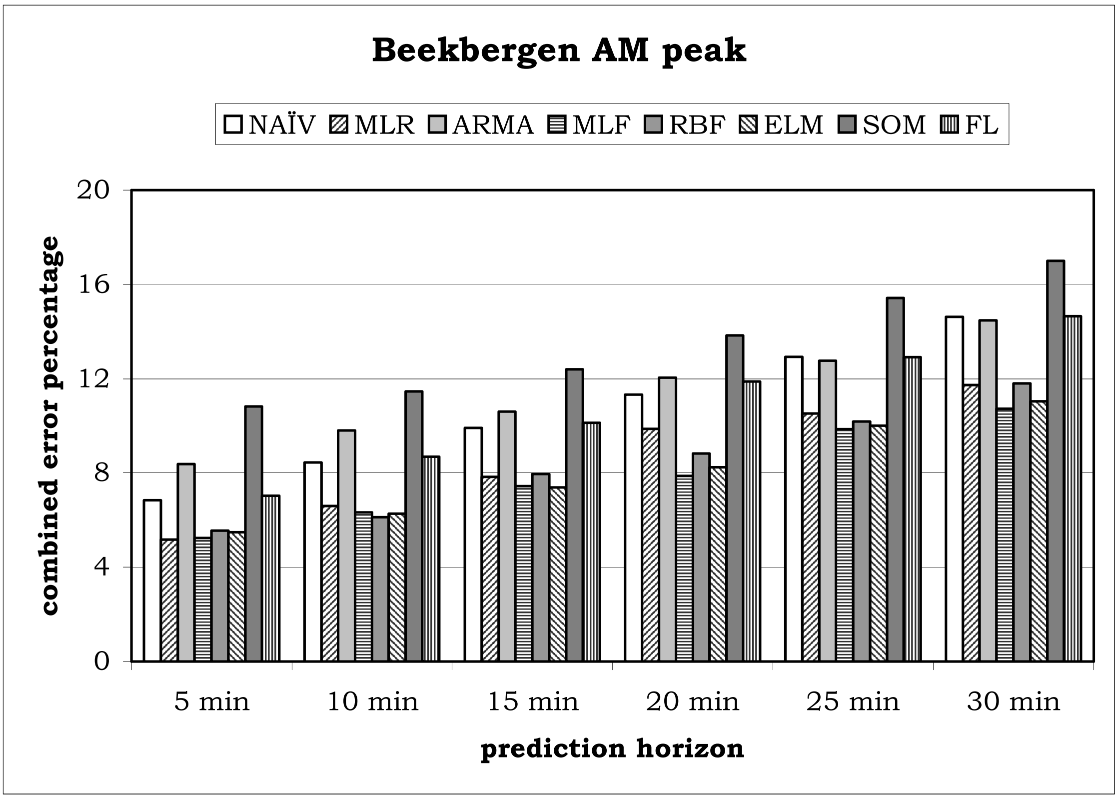

Figure 8.33: Combined results for the Beekbergen AM peak period.

The results of the Beekbergen AM peak period show that as the prediction horizon gets longer, the error percentages increase. This is true for all methods. The SOM models produce the worst results. The results of the naïve models are more or less comparable to those of the ARMA models and the FL models, however, when the prediction horizon is short the ARMA and FL models are slightly outperformed by the naïve models. MLR models outperform the ARMA and FL models and are surpassed by the supervised ANN models. The score of the MLF models and the Elman models is almost similar; they both produce slightly better results than the RBF models.

The target detector at the Beekbergen location has defined about 17.9 % of the time (all recorded morning peak periods) as congested traffic. This target detector reports on a typical bottleneck location (going westbound on motorway 1 from Deventer towards Apeldoorn, the bottleneck is located where the 3-lane motorway reduces to a 2-lane motorway) where additional information coming from upstream detectors is present (see 6.3 and appendices E, F and J). Under these circumstances the supervised ANN models give the best predictions.

The fact that SOM models, FL models and ARMA models are equally good as or are outperformed by the naïve models means that these models do not have added value under the circumstances as describe above and should therefore not be considered as a prediction tool.

8.10.2 Beekbergen PM peak period

Figure 8.34 shows the combined error results of all Beekbergen models during the evening peak period for each prediction horizon.

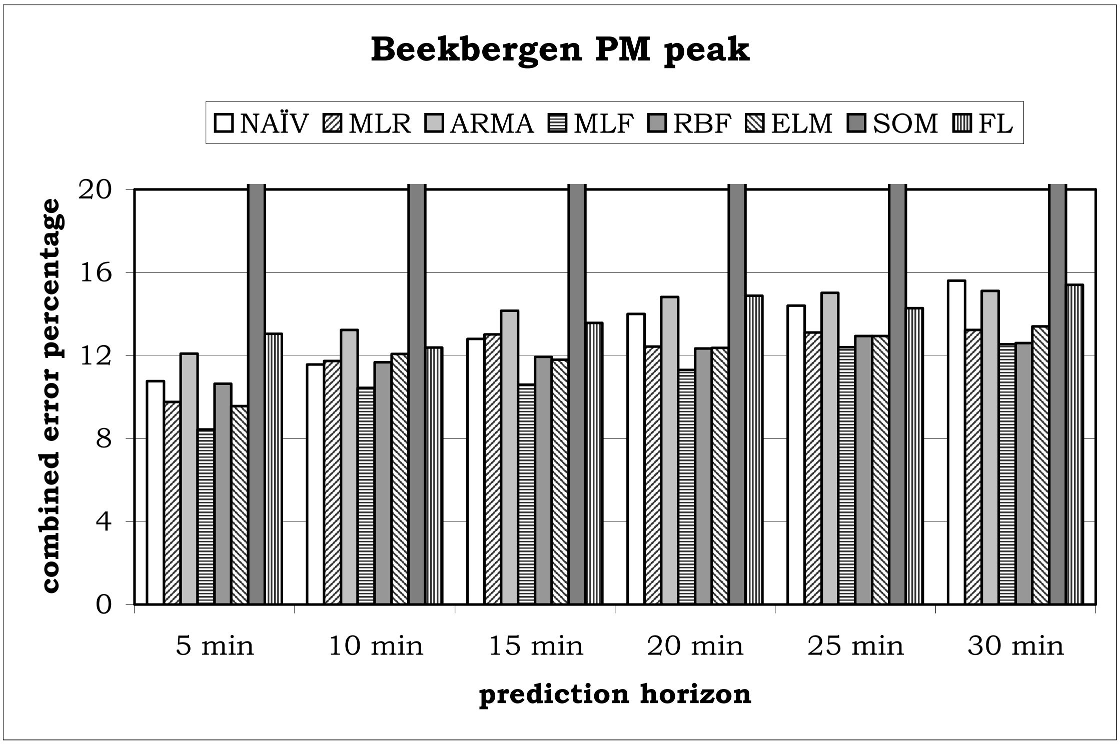

Figure 8.34: Combined results for the Beekbergen PM peak period.

The combined error percentages of all models increase as the prediction horizon gets longer. However, for most models the error does level off when the prediction horizon reaches 20 minutes and beyond. Also, the SOM models (again) produce the worst results, while the supervised neural network models reach the best results.

The mean percentage of congested traffic time reported by the target detector is 14.3 % of the evening peak period. During the evening peak, large volumes of traffic travel northbound on motorway 50 (coming from the city of Arnhem and beyond) and eastbound on motorway 1 (coming from the city of Apeldoorn and beyond), both streams are headed eastbound on motorway 1 towards destination Deventer and beyond. These traffic streams meet at the location of the target detector and therefore this is the spot where congestion usually sets in (see appendices E, G and J). Hence the target detector is the premier detector to report congestion. As figure 8.34 shows, the supervised neural network models produce the best congestion prediction results for this kind of merging traffic.

8.10.3 Hoevelaken AM peak period

Figure 8.35 shows the combined error results of all Hoevelaken models during the morning peak period for each prediction horizon.

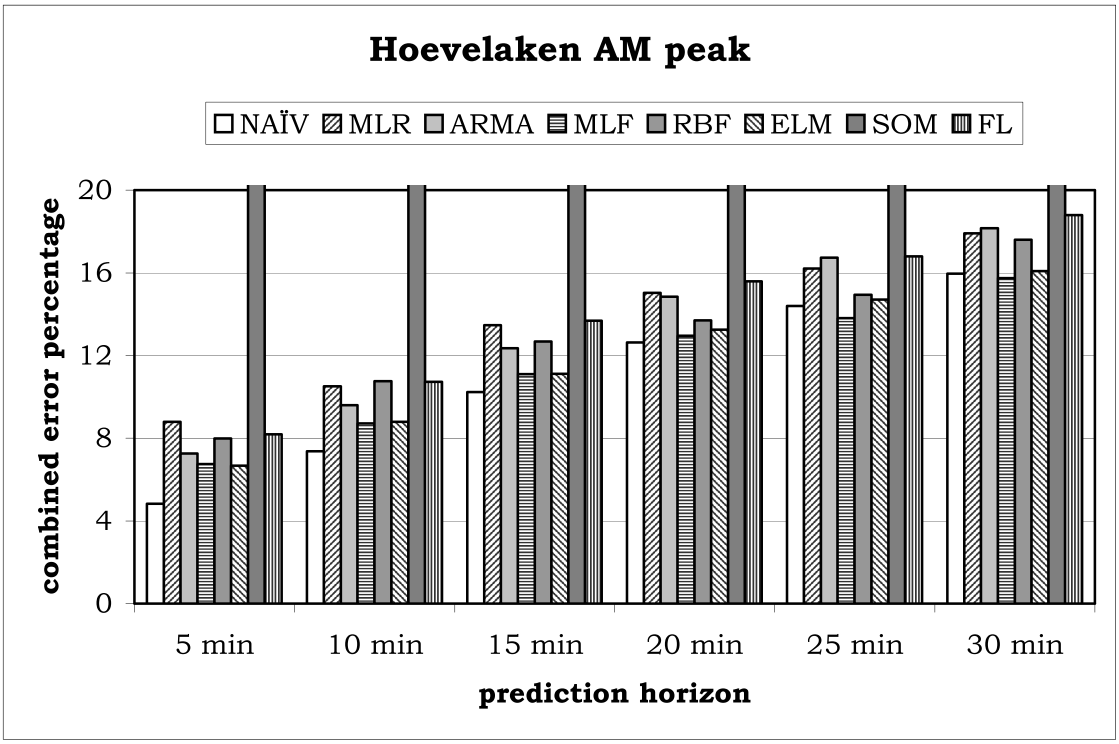

Figure 8.35: Combined results for the Hoevelaken AM peak period.

The combined error percentages of all models increase as the prediction horizon gets longer. The error increase is almost linear for all models for the entire prediction horizon range. Also, the SOM models (again) produce the worst results, while the naïve models and the supervised neural network models reach the best results.

The target detector suffers congestion for 26.2 % of the time during morning peak periods. During the morning peak, large volumes of traffic travel southbound on motorway 28 (coming from Zwolle and beyond) and westbound on motorway 1 (coming from Apeldoorn and beyond), both streams are heading southbound on motorway 28 towards destinations Amersfoort, Utrecht and beyond. These traffic streams meet at the location of the target detector and therefore this is the spot where congestion usually sets in (see appendices E, H and J). Hence the target detector is the premier detector to report congestion. As figure 8.35 shows, the naïve models and the supervised neural network models produce the best congestion prediction results for this kind of merging traffic.

When congestion sets in, the target detector reports on long periods of traffic congestion (see again appendix H). This kind of congestion presents the naïve models with a big advantage in that they produce errors for only 5 minutes at the beginning of the congestion phase and 5 minutes immediately after the congestion phase has ended.

8.10.4 Hoevelaken PM peak period

Figure 8.36 shows the combined error results of all Hoevelaken models during the evening peak period for each prediction horizon.

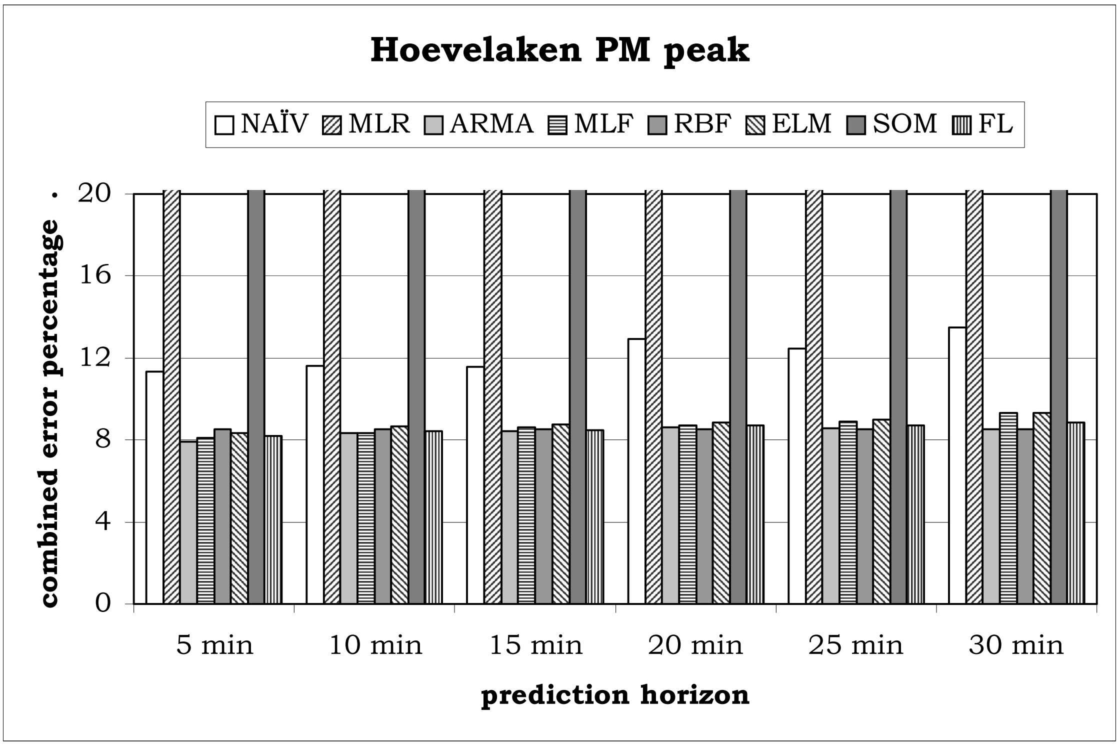

Figure 8.36: Combined results for the Hoevelaken PM peak period.

Contrary to intuition and to the results seen before, the combined error percentages of all models stay stationary during the evening peak at Hoevelaken as the prediction horizon gets longer. Also striking is the order of magnitude of the error percentages produced by the models.

Except for the SOM models, the results of the combined error percentages are virtually the same for all models. As before the SOM models (again) produced the worst results.

The traffic situation at the location of the target detector is during the evening peak period reported by the detector as congested for 8.5 % of the time. During these peak periods, large volumes of traffic travel northbound on motorway 28 (coming from Amersfoort, Utrecht and beyond) and eastbound on motorway 1 (coming from Amersfoort, Amsterdam, in-between both cities and beyond), both streams are headed eastbound on motorway 1 towards destinations Apeldoorn and beyond. These traffic streams meet at the location of the target detector and therefore this is the spot where congestion usually sets in (see appendices E, I and J). Hence the target detector is the premier detector to report congestion. As figure 8.36 shows, all models with the exception of the naïve models and the SOM models produce equal congestion prediction results for this kind of merging traffic.

The traffic situation at the location of the target detector is during the evening peak period defined as congested for 8.5 % of the time. When congestion sets in, the target detector reports on typical stop-and-go traffic congestion (see section I). This kind of congestion is difficult to predict with one minute accuracy, especially when the prediction horizon increases. Most models are not capable of predicting stop-and-go congestion when the target detector reports ‘congestion’ for 2-4 minutes followed by ‘no congestion’ for 4-7 minutes, etcetera. The naïve models are particularly vulnerable to this kind of congestion, because every event (a congestion phase) can result in a 10-minute period of wrong outcome, especially when the duration of the congestion period is 5 minutes or shorter. This can be verified by looking at the results displayed in figure 8.36.

Another explanation for the results was already stated in 8.5: the aggregated period of congestion that was reported by the target detector has a low percentage of time and since it is also stop-and-go congestion, the best overall results that the models are able to produce is when their outcome is ‘no congestion’ for (almost) the entire period. In addition, the downstream directions of both big volume traffic streams are not equipped with detectors. Hence, there is virtually no information on traffic upstream. This makes it very difficult to predict the state of traffic at the target detector within the short-term.

Whenever a target detector reports congestion for a low percentage of the time, and when the nature of this congestion is stop-and-go congestion for the majority of the time and there are few detectors upstream of the target detector, it is hard to predict stop-and-go congestion with an interval of one minute accuracy. A congestion prediction tool should therefore not be build with a model that is based on the methods researched in this study. A possible solution might be to change the data acquisition time bin lengths from one minute to, say, five minutes and to change the prediction time steps accordingly, however, this should be subject of further research before conclusions can be drawn.

8.11 Sensitivity analysis

In this section the sensitivity of the models will be analyzed by:

- Checking the model parameters: the statistical properties of the multi linear regression models and the weights of the input neurons of supervised ANN's (the 1st phase of pruning the neural networks with a technique known as 'optimal brain damage', see e.g. LeCun *et al.*, 1990; Guo and Liu, 2003, or the more advanced technique 'optimal brain surgeon', see Hassibi and Stork, 1993);
- Stretching target data by transforming periods of 'not congested' into 'congested' if these periods are shorter than x minutes (x = 1, 2, …, 5 minutes).

The combination of these analyses can shed light on the sensitivity of the models and their variables, more so because the ANN models are regarded as "black boxes" with respect to their internal working method. The sensitivity analyses with the pruning technique can be used to make ANN models less "black", while the target data stretching can be used to gain additional knowledge on data aggregation levels.

8.11.1 Checking the model parameters

Statistical properties of the multi linear regression models

Here some statistical properties of the MLR models are analysed. The R-square statistic, the F-statistic, the p-value and an estimate of the error variance are computed.

Table 8.1: *Statistical properties of the MLR models.*

Location	*Peak*	*Prediction horizon*	*R^2*	*F*	*p*	*Error variance*
Beekbergen	AM	0 minutes	0.8435	157.5	< 0.001	0.0237
		5 minutes	0.7234	76.41	< 0.001	0.0418
		10 minutes	0.6763	61.14	< 0.001	0.0489
		15 minutes	0.6233	48.32	< 0.001	0.0569
		20 minutes	0.5802	40.37	< 0.001	0.0633
		25 minutes	0.5281	32.70	< 0.001	0.0712
		30 minutes	0.4803	27.01	< 0.001	0.0784

Location	*Peak*	*Prediction horizon*	R^2	*F*	*p*	*Error variance*
Beekbergen	PM	0 minutes	0.7060	50.70	< 0.001	0.0362
		5 minutes	0.5266	23.44	< 0.001	0.0586
		10 minutes	0.4452	16.94	< 0.001	0.0688
		15 minutes	0.4219	15.35	< 0.001	0.0719
		20 minutes	0.3965	13.90	< 0.001	0.0748
		25 minutes	0.3744	12.66	< 0.001	0.0776
		30 minutes	0.3553	11.72	< 0.001	0.0799
Hoevelaken	AM	0 minutes	0.8540	114.7	< 0.001	0.0748
		5 minutes	0.7465	55.58	< 0.001	0.1305
		10 minutes	0.6763	39.40	< 0.001	0.1664
		15 minutes	0.6091	29.33	< 0.001	0.2012
		20 minutes	0.5604	24.05	< 0.001	0.2262
		25 minutes	0.5306	21.33	< 0.001	0.2417
		30 minutes	0.5050	19.24	< 0.001	0.2552
Hoevelaken	PM	0 minutes	0.6083	32.23	< 0.001	0.0817
		5 minutes	0.2476	6.841	< 0.001	0.1570
		10 minutes	0.2103	5.530	< 0.001	0.1649
		15 minutes	0.1889	4.834	< 0.001	0.1694
		20 minutes	0.1664	4.143	< 0.001	0.1741
		25 minutes	0.1588	3.921	< 0.001	0.1758
		30 minutes	0.1365	3.282	< 0.001	0.1804

The results of both the R-square and error variance show that the predictive power deteriorates with increasing prediction horizon. The pattern that is revealed in table 8.1 is consistent with the results described in 8.3.

How can the importance of each individual input variable against another be assessed? The normalised t-values of the input variables of the MLR models were determined first. For each of the four sub-models the same input variables should have comparable significance. If that is the case; how the significance changes with increasing prediction horizon is tested by comparing the mean input variable significance per prediction horizon of the morning peak period of the Beekbergen location. If not, comparisons of sub-model input significance values against each other will be made. Finally which findings are transferable to other locations will be determined.

First, the t-values of the input variables of the first MLR sub-model are determined for the 0-minute prediction horizon of the Beekbergen morning peak period after which these values are normalised (thus adding up to one). Graphically the input variables can be displayed as a one-dimensional line of 150 points or a two-dimensional grid of 15 (detectors) * 10 (detector variables). Since the one-dimensional line will give a better view as the prediction horizon increases (when those lines are displayed one above the other as in figure 8.32).

The significance values of the input variables for the four MLR sub-models at the 0 minute prediction horizon are shown in figure 8.37.

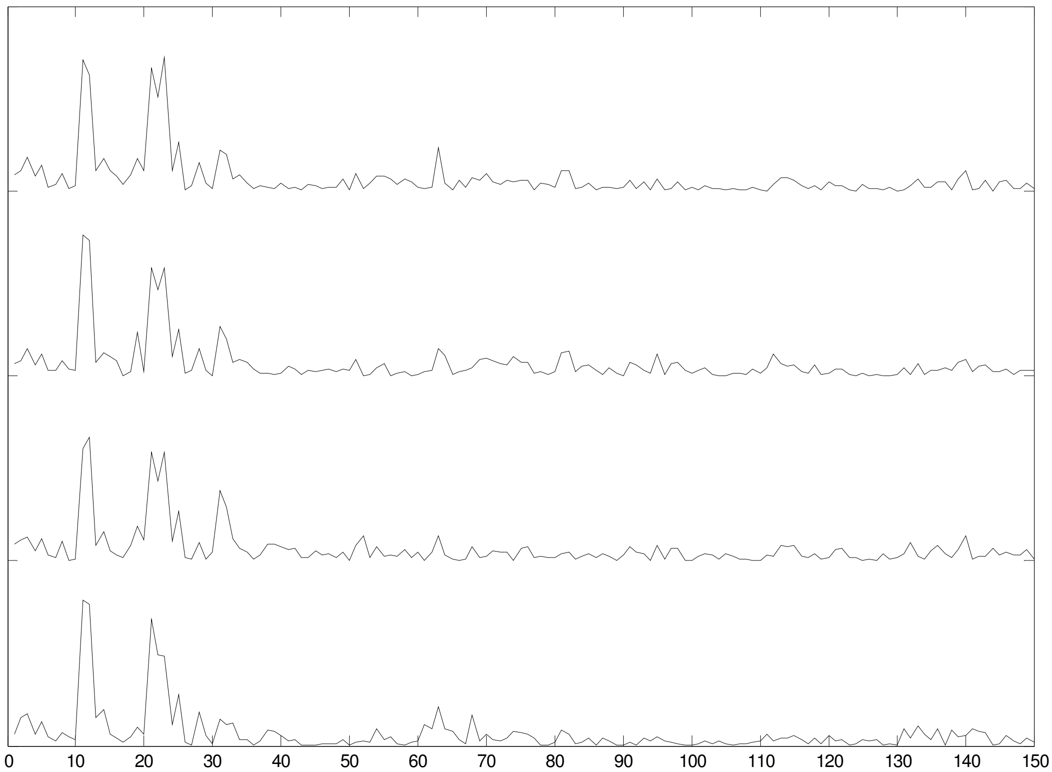

Figure 8.37: Normalised absolute significance values of input variables of the four MLR sub-models of the 0-minute prediction horizon of the Beekbergen AM peak period.

The lines, representing the significance values of the input variables of the MLR sub-models, are comparable in magnitude for corresponding input variables. Therefore the mean of the significance values of the four sub-models gives significance values of the aggregated MLR model at the 0-minute prediction horizon of the Beekbergen AM peak period (figure 8.38).

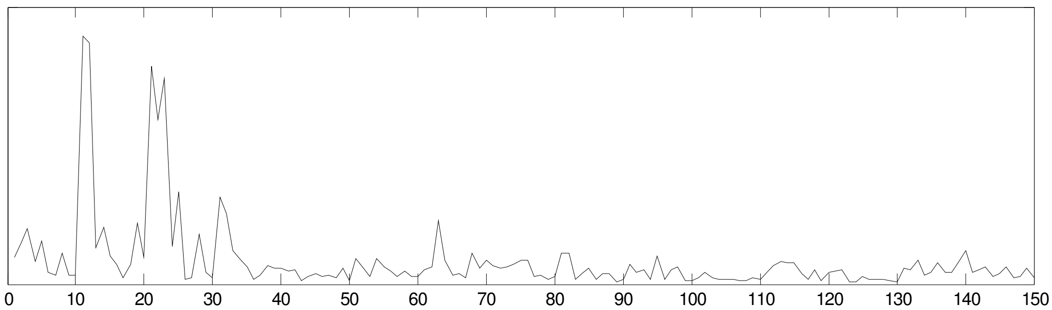

Figure 8.38: Normalised absolute significance values of input variables of the MLR model of the 0-minute prediction horizon of the Beekbergen AM peak period.

The significance of the input variables that represent the second and third detector (numbered 11 – 30) are noteworthy. The input variables that are most significant are the first two of the second detector, representing occupancy of all traffic and intensity of vehicles with a length shorter than 5.10 meters, and the first three of the third detector, representing occupancy of all traffic and intensity and speed of vehicles with a length shorter than 5.10 meters. The second detector is the target detector itself (with original detector number 45; on the middle, i.e. the second lane of the motorway) and the third detector is lying one lane right of it (with original detector number 46 – the 'slow' traffic lane, see paragraph 6.3. and appendices E and J). It appears that the congestion state of the target detector is best described by the traffic state indicator for cars in close proximity to the target detector, as one would expect.

Figure 8.39 displays the normalised significance values for corresponding input variables by increasing prediction horizon; i.e. the top line represents the 0-minute prediction horizon, while the 30-minute line is situated at the bottom.

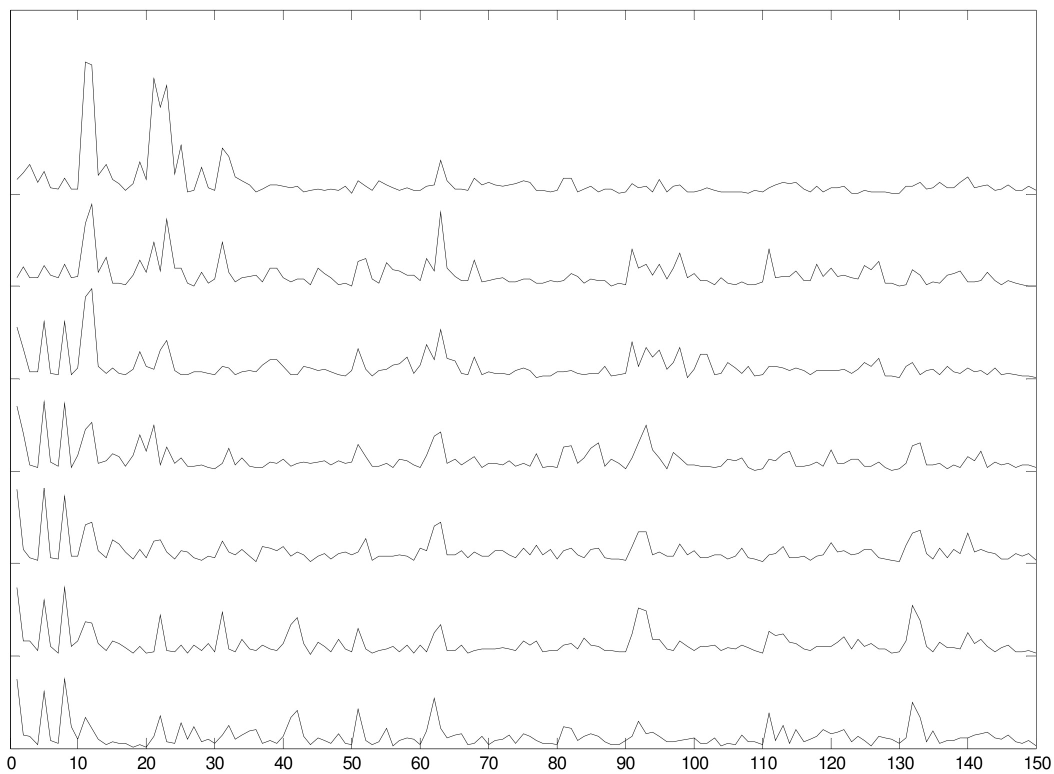

Figure 8.39: Normalised absolute significance values of input variables of the MLR models for all prediction horizons of the Beekbergen AM peak period; the top line represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom line.

The magnitude of the initial significant detectors and their input variables diminishes. The 5-minute prediction horizon line shows relatively more significance at upstream detectors 5 and 7 while when reaching the 15-minute prediction horizon line, the input variables belonging to detector 10 (further upstream; numbered 91 – 100) gain relatively more significance. Traffic on the ‘high’ speed lane, left of the target detector, is also becoming increasingly significant. Beyond the 15-minute prediction horizon the patterns of the lines stay more or less identical.

For the 0-minute prediction line, the intensity input variable of up to 5.10 metres vehicles of the target detector is determined to be the most significant one. However, at the 5-minute and 10-minute prediction horizon it is the intensity of the vehicles with a length up to 5.10 metres that scores as most significant.

Figure 8.40 shows the results of the significant value determination of the input variables of location Beekbergen obtained during the evening peak period.

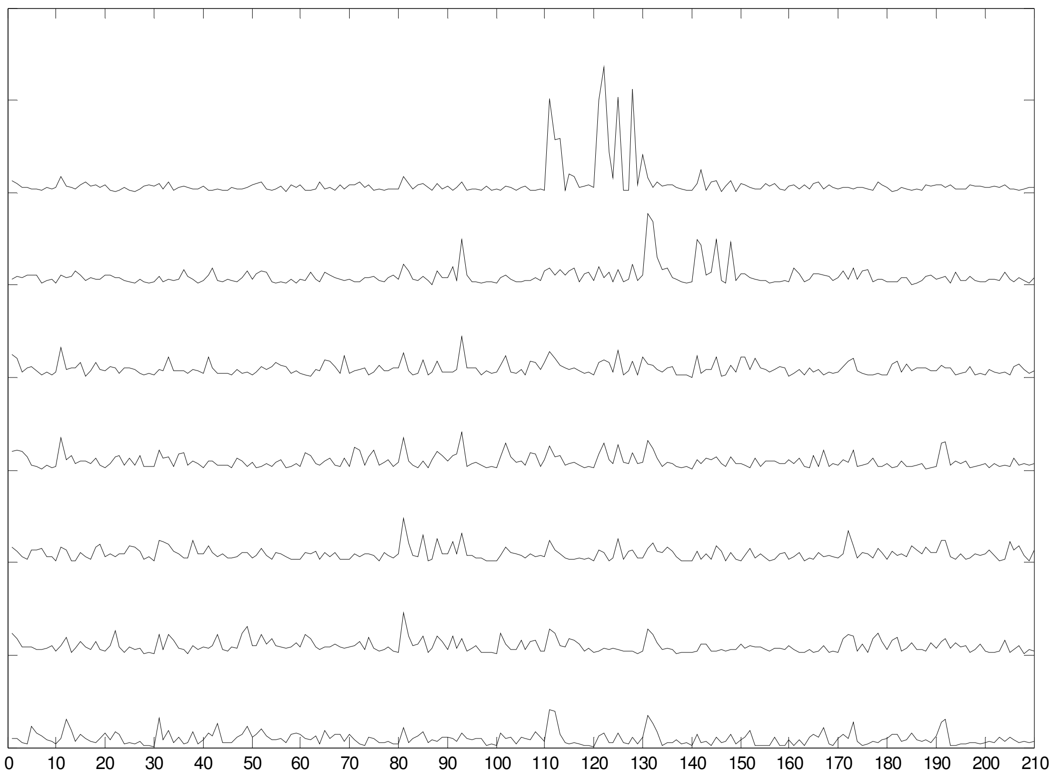

Figure 8.40: Normalised absolute significance values of input variables of the MLR models for all prediction horizons of the Beekbergen PM peak period; the top line represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom line.

The 0-minute prediction horizon shows many non-significant input variables. The most significant detectors are the 12th and the 13th loop detector (numbered 111 – 130). The 12th detector is the target detector, whereas the 13th detector is lying directly right of the target detector, see 6.3 and appendices E and J. The 14th and 15th detector are the first loop detectors to encounter upstream and the significance is increasing when the 5-minutes prediction horizon line is reached. Also, the 10th detector (input numbers 91 – 100) is gaining in significance at this prediction horizon. When the 20-minute prediction horizon is reached, the 9th detector gains significance, while this detector is representing a loop detector further upstream.

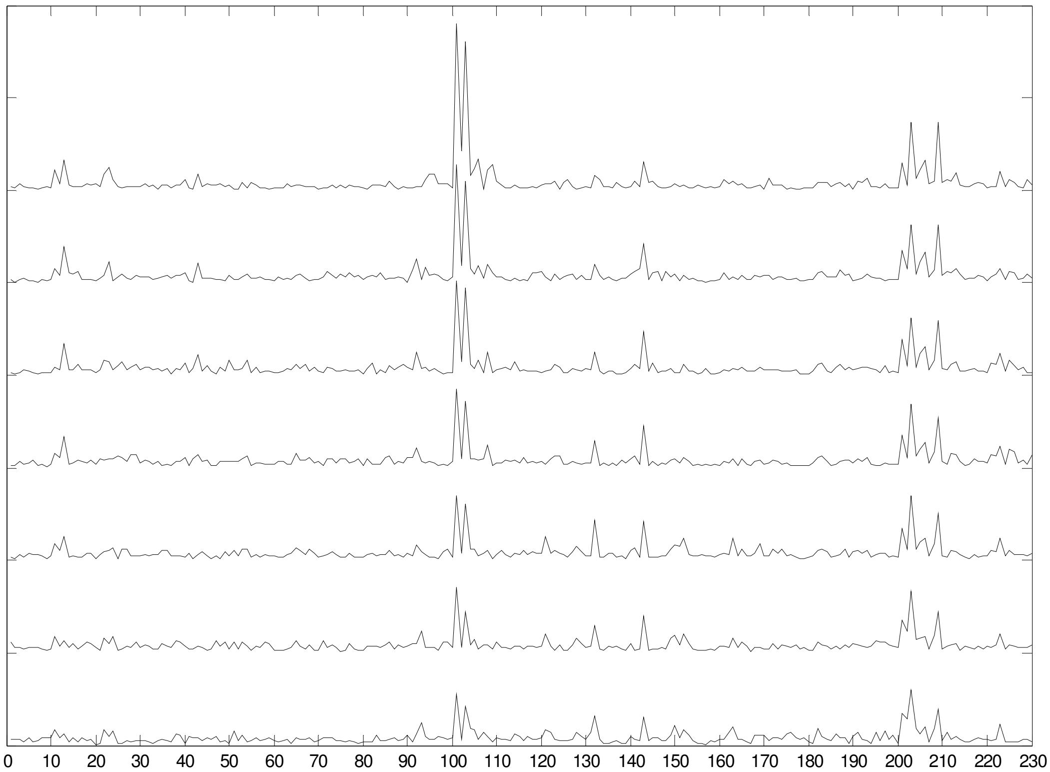

Figure 8.41: Normalised absolute significance values of input variables of the MLR models for all prediction horizons of the Hoevelaken AM peak period; the top line represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom line.

The pattern in figure 8.41 is very different from figures 8.39 and 8.40. It is more static: the same detectors stay the most significant with time, although the magnitude of significance decreases. Interestingly, the 3rd detector is representing the target detector (input numbers 11 – 20) and its significance is not that obvious. However, the target detector suffers from congestion for long periods and the local speed is very low. The loop detector that suffers from congestion immediately after the target detector reports congestion is the 11th detector (the next downstream detector). As the prediction horizon increases, also the 14th detector gains significance. The 14th detector lies upstream on motorway A28 just before the junction with motorway A1 (see 6.3 and appendices E and J).

The evening peak at the Hoevelaken location shows an entirely different pattern (figure 8.42), keeping in mind that the 9th detector represents the target detector.

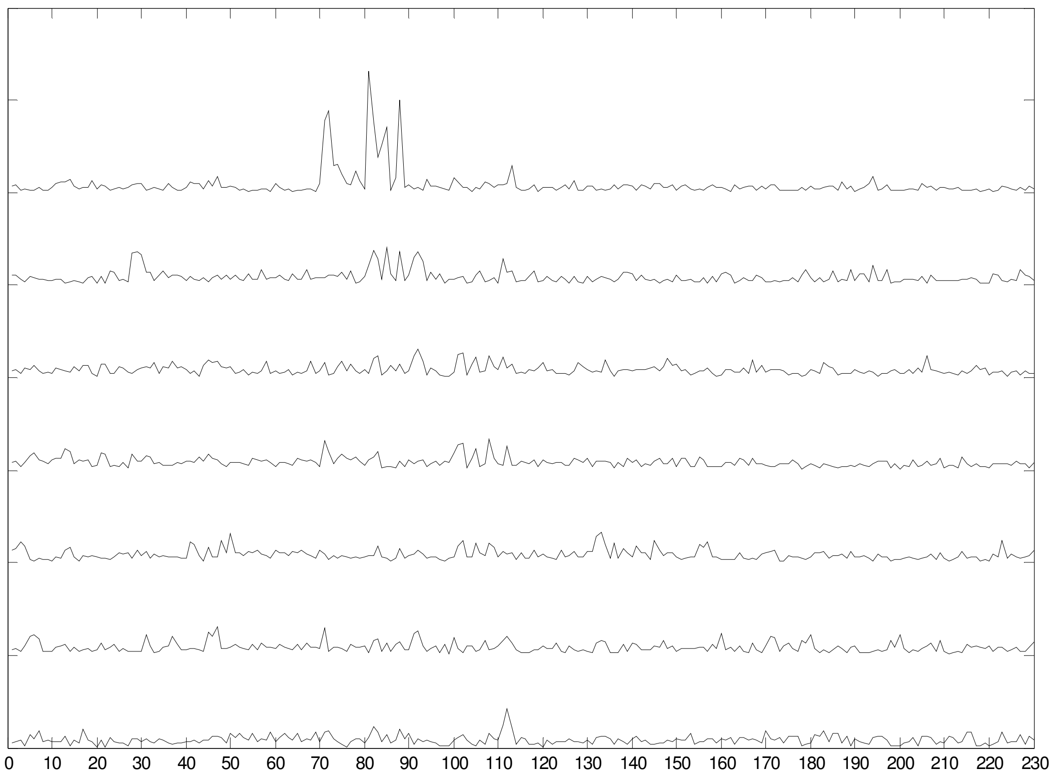

Figure 8.42: Normalised absolute significance values of input variables of the MLR models for all prediction horizons of the Hoevelaken PM peak period; the top line represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom line.

When the 0-minute prediction horizon line is considered, the significance of the 8th and the 9th detector are clear and present. When the prediction horizon increases by only 5 minutes, the magnitude of significance of those detectors deteriorates quickly and spreads towards upstream detectors (the 11th and 12th detector with input numbers 101 – 120) that gain small magnitudes of significance. When the 20-minute prediction horizon line is reached, the 14th detector becomes relative more significant; beyond the 20-minute prediction horizon line no apparent changes are visible. However, when comparison of figures 8.8 and 8.42 shows that further discussion is meaningless due to the (bad) prediction results of the MLR models at the Hoevelaken location during the evening peak (probably due to singularity).

Optimal Brain Damage / Optimal Brain Surgeon

'Optimal brain damage' and 'optimal brain surgeon' are techniques that are applied to artificial neural networks. Both techniques imply that unimportant connections are terminated. Because these connections do not contribute to the output, they might as well be removed whilst the result / output of the models will still be almost identical to the output of the intact models, hence the name 'optimal brain damage' or 'optimal brain surgeon'. This leads to the conclusion that the examination of the weights of the neurons that make up the first layer will give clues about the importance of those input neurons and therefore of the importance of the input variable.

There is, however, a flaw in the reasoning above. It concerns a step taken during the pre-processing phase: the normalisation step. If the weights are close to zero then the reasoning holds, or, more precisely, if the values of the weights of the first layer are within the proximity of zero, the input neuron can be considered unimportant. If not, the absolute value of the weight is likely, but not necessarily, to be linked directly to the importance of the parameter at hand. If some weights are significantly bigger than other weights, this is an indication that the associated variables are the most important ones.

We have already established the ANN architecture for the MLF model that provided the best results; see 7.4. For the Beekbergen location during the morning peak period this resulted in an MLF model with architecture of 150 – 6 – 1 neurons. In figure 8.43, the weight strengths of the layer between the 150 and 6 neurons of the four sub-models for the 0-minute prediction horizon are shown. Clearly, the weights of the sub-models are very similar.

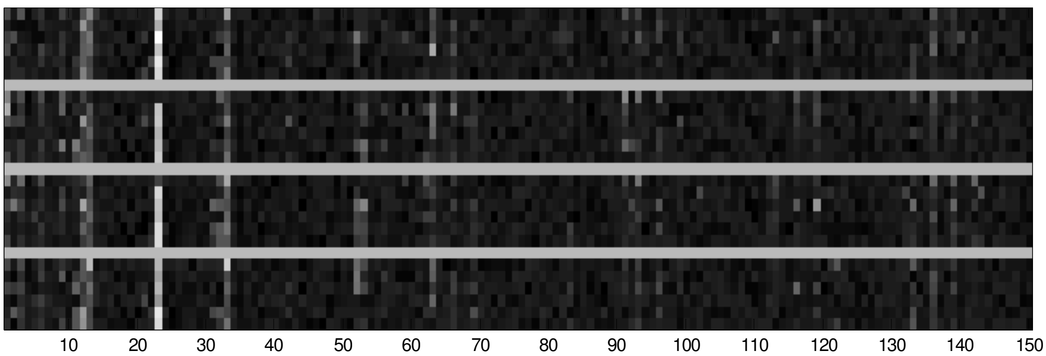

Figure 8.43: Normalised absolute values of the weights of the layer between the 150 input neurons and the 6 hidden neurons of the four MLF sub-models of the 0-minute prediction horizon of the Beekbergen morning peak period.

The normalised absolute values of the weights of the layer between the input and hidden neurons of the four sub-models show similar patterns (figure 8.43) and their mean gives the weights of a mean model for 0-minute congestion prediction of the Beekbergen morning peak period with an MLF model; the resulting weights (figure 8.44).

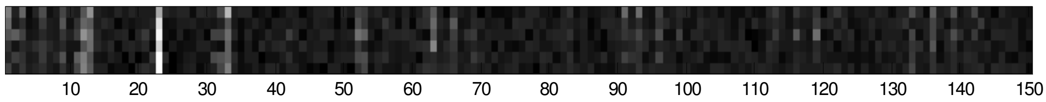

Figure 8.44: Normalised absolute values of the weights of the layer between the 150 input neurons and the 6 hidden neurons of the MLF model of the 0-minute prediction horizon of the Beekbergen AM peak period.

Figure 8.45 shows the weights of the 0-minute prediction horizon as the top strip, followed by the 5-minutes prediction horizon until the 30-minutes prediction horizon is reached as displayed by the bottom strip of the figure.

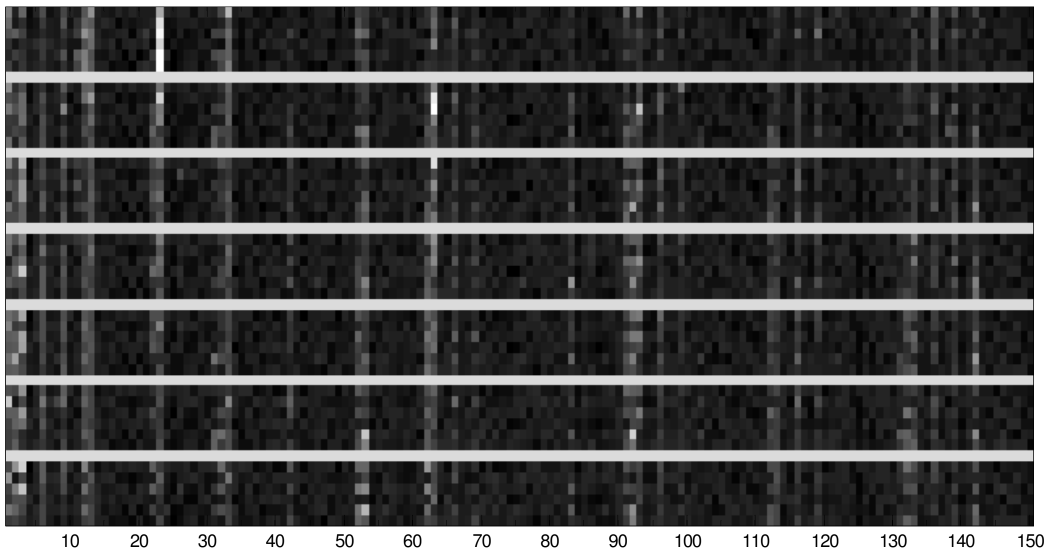

Figure 8.45: Normalised absolute values of the weights of the layer between the 150 input neurons and the 6 hidden neurons of the MLF models for all prediction horizons of the Beekbergen AM peak period; the top strip represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom strip.

The third detector has one high value and therefore a significant input variable: the mean speed of the vehicle class with the shortest length (ordinary cars). Also, the 1st, 2nd and 4th detectors are significant, all with input variable mean speed (the significant input variables of the 1st detector are the mean speed variables of all vehicle classes). The 5-minutes prediction horizon shows that the significant magnitude of the 3rd detector has deteriorated and the levels of the 1st and 7th detector have gained significance. As the prediction horizon gets longer, the 10th detector gains significance and when the 20-minute prediction horizon is reached, the pattern stays more or less identical. Again, significance levels that are high for the target detector in the 0-minute prediction horizon can be seen. The levels then deteriorate and spread out to loop detectors upstream of the target detector.

Figure 8.46 below shows the normalised absolute values of the weights of the MLF models for the Beekbergen evening peak period.

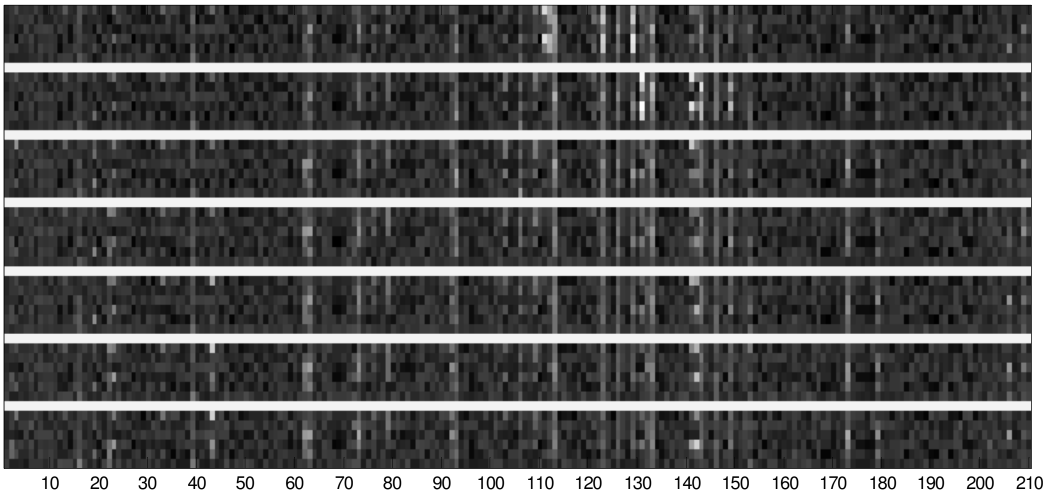

Figure 8.46: Normalised absolute values of the weights of the layer between the 210 input neurons and the 6 hidden neurons of the MLF models for all prediction horizons of the Beekbergen PM peak period; the top strip represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom strip.

The 12th detector is the target detector. It can be clearly seen that the 11th, 12th, and 13th detectors have the highest weight values and thus are the most significant. Again, the mean speed variables are the input variables that matter the most. When the 5-minute prediction horizon is reached, the 13th, 14th, and 15th detector show the most significance. The pattern that is shown at the 10-minute prediction horizon, where the high values of the input variables belonging to the 13th and 14th detector have somewhat deteriorated, stays more or less stationary for the longer prediction horizons.

The conclusion is reached that figures 8.40 and 8.46 share similarities concerning the main issues. Both figures show high significance for the target detector and the detectors in its immediate vicinity at the 0-minute prediction horizon. Also, when the prediction horizon increases, the significance of upstream detectors gains value that slowly deteriorates when the prediction horizon gets longer. In fact, this pattern can be seen for both the morning and evening peak at the Beekbergen location. The difference between the MLR models and the MLF ANNs is the significance of the detector variables. While for the MLR models occupancy and intensity are the most significant, the mean speed of, in most cases all, but definitely the smallest vehicle class is most important for the MLF ANNs.

The next figure presents the normalised absolute values of the weights of the layer between the input and hidden neurons of the MLF models of the Hoevelaken morning peak period. The 3rd detector is the target detector, while the 14th detector is the first detector downstream of the target detector, just before the junction of motorway A28 and motorway A1. The 10th detector is the first detector downstream of the target detector.

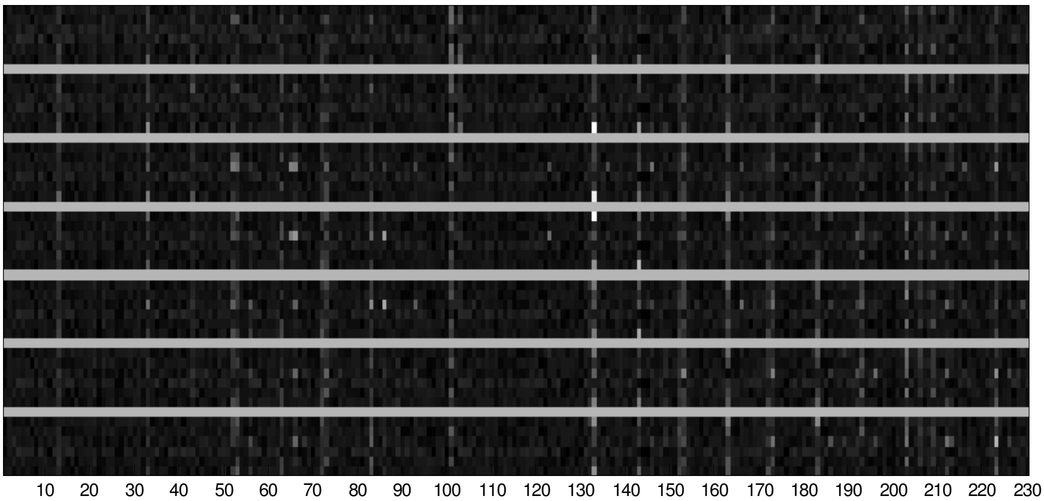

Figure 8.47: Normalised absolute values of the weights of the layer between the 230 input neurons and the 6 hidden neurons of the MLF models for all prediction horizons of the Hoevelaken AM peak period; the top strip represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom strip.

Again, there is a high resemblance to the MLR models' significance findings. The same detectors acquire the most important data, while the pattern that is formed at the 0-minute prediction horizon is more or less stationary throughout the prediction horizon increase up to 30 minutes. Also, the 3rd variable (representing the mean speed of the smallest vehicle class) of the most significant detectors are the input variables that have the highest values.

The normalised absolute values of the weights of the first layer of the MLF models for the evening peak period at the Hoevelaken location are displayed in figure 8.48. At this location during the evening peak period, the 9th detector represents the target detector.

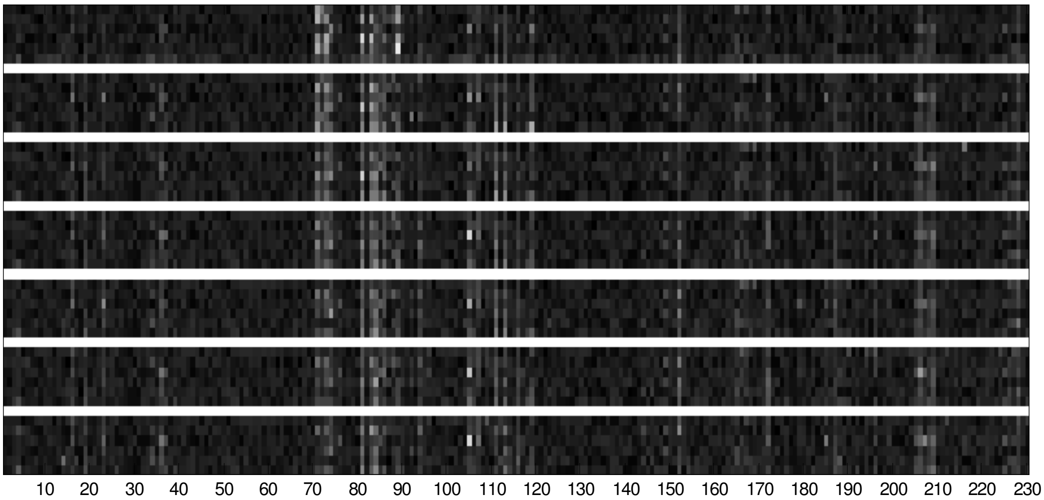

Figure 8.48: Normalised absolute values of the weights of the layer between the 230 input neurons and the 6 hidden neurons of the MLF models for all prediction horizons of the Hoevelaken PM peak period; the top strip represents the 0-minute prediction horizon, while the 30-minute prediction horizon is represented by the bottom strip.

In the top strip the 8th and 9th detectors can be clearly distinguished as being the most significant ones. When the prediction horizon increases, a different pattern than with the MLR models of the Hoevelaken evening peak period can be seen: figure 8.48 shows a slow deterioration of the significance of the target detector and the significant ones just upstream of it (the 11th and 12th detector). However, the MLR models did suffer from singularity and are therefore not relevant. It is also know that the MLF models of the Hoevelaken evening peak period are of no practical importance in that they do not capture congestion adequately due to the low percentage of congestion in the training sets. In short: congestion prediction at the Hoevelaken location during the evening peak period is not possible through the methods used and the target data that were acquired during the month of May 2001.

8.11.2 Stretching target data

The outputs of the models that were presented in 8.2 – 8.10 (based on data acquired into one minute time bins) were transformed to 'new' outputs, where gaps of '*x* minutes' (x = 1, 2, …, 5) are recoded from 'not congested' to 'congested' by applying the next set of rules:

For '*x*-minute gap':

IF target$_{(x\text{ minutes gap})}$ = “not congested”
THEN period$_{(x\text{ minutes gap})}$ = “congested”

The goal of this operation is to get clues about the optimum aggregation level of the acquisition time bins. Click *et al.* (1997) reported an optimum of 1 minute time bins for congestion prediction purposes (see also chapter 6). However, the data used in that particular study is not as rich as the MoniCa data that is present in this study and acquisition levels may have a different optimum for the models to predict congestion accurately. This assumption can be checked by filling non-congested gaps of 1 to 5 minutes in order to mimic larger acquisition time bins and to assess these pseudo-aggregation levels. The results for the Beekbergen morning peak are displayed in figures 8.49 – 8.53 and can also be found in appendix K, as well as the results of the remaining peak periods.

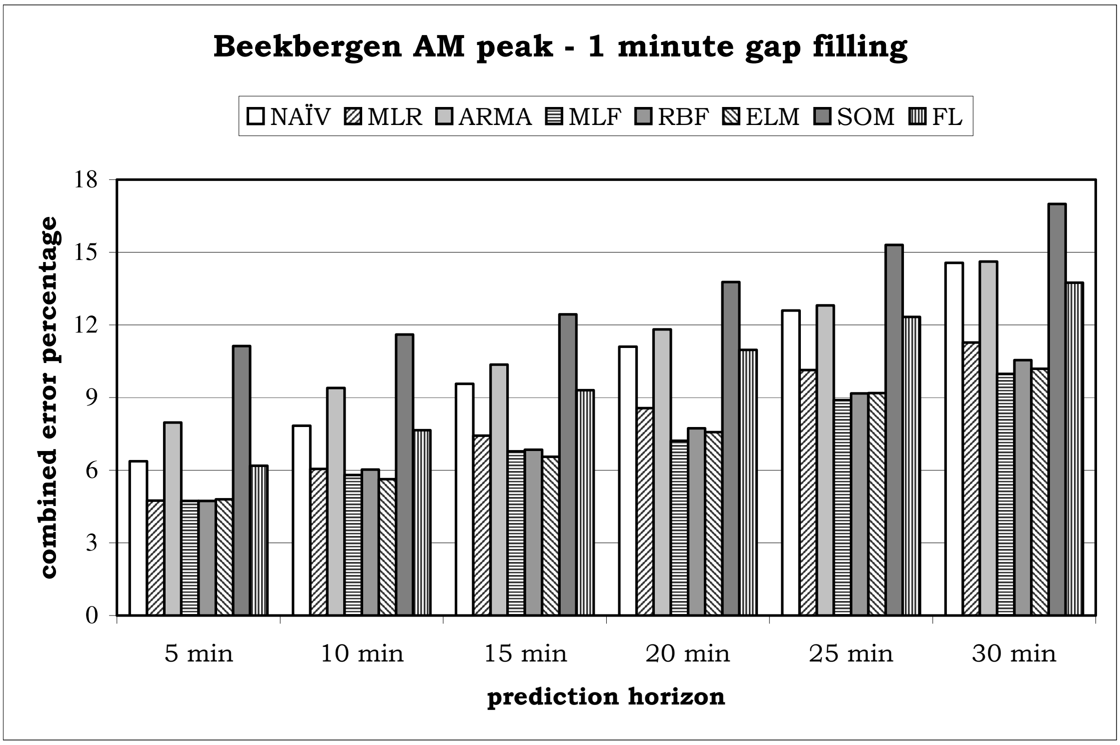

Figure 8.49: Combined results for the Beekbergen AM peak period, where ‘not congested’ gaps of 1-minute duration are transformed to ‘congested’.

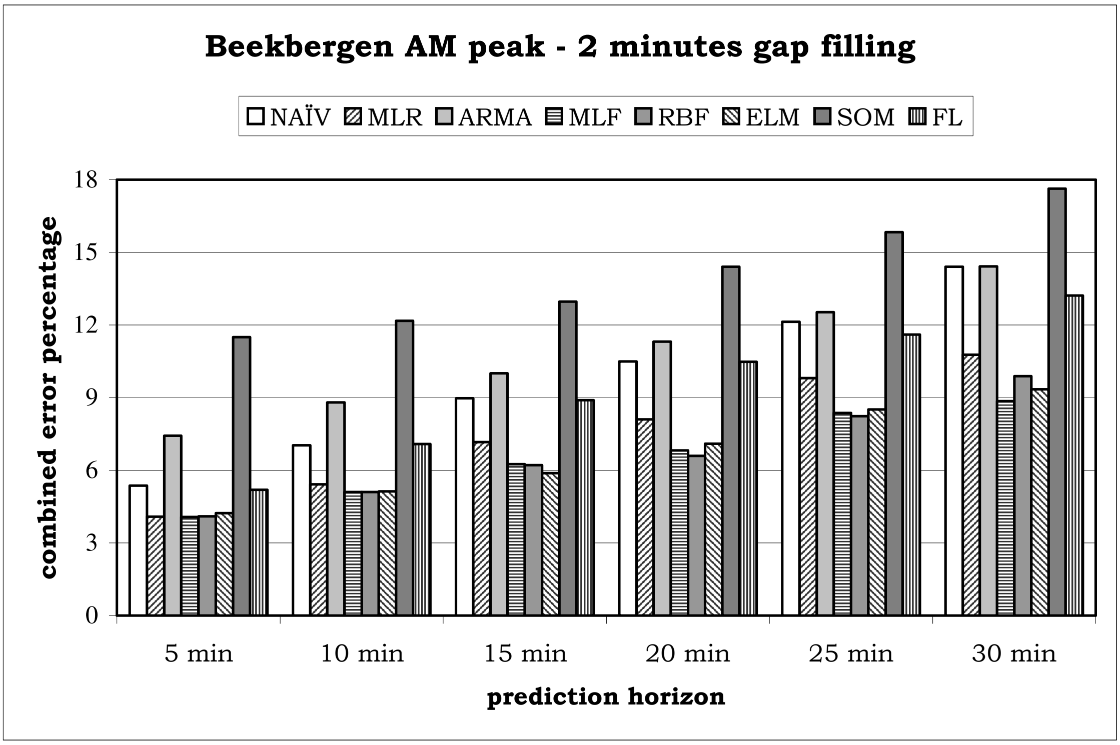

Figure 8.50: Combined results for the Beekbergen AM peak period, where 'not congested' gaps of 2-minute (or less) duration are transformed to 'congested'.

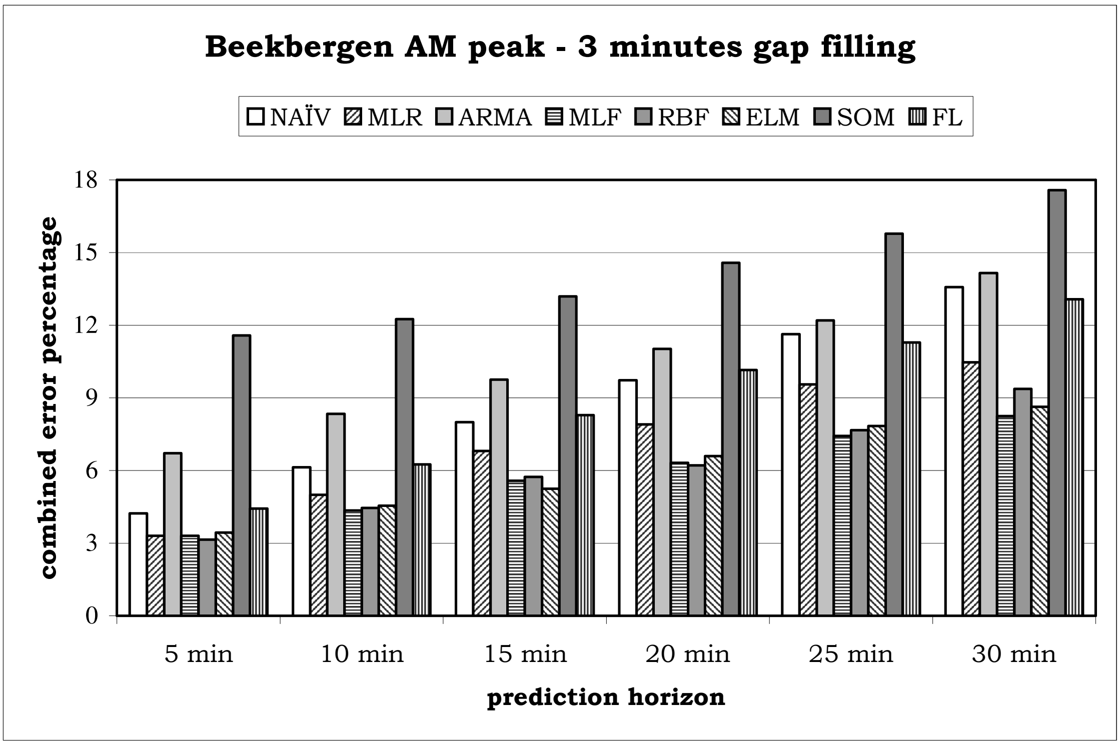

Figure 8.51: Combined results for the Beekbergen AM peak period, where 'not congested' gaps of 3-minute (or less) duration are transformed to 'congested'.

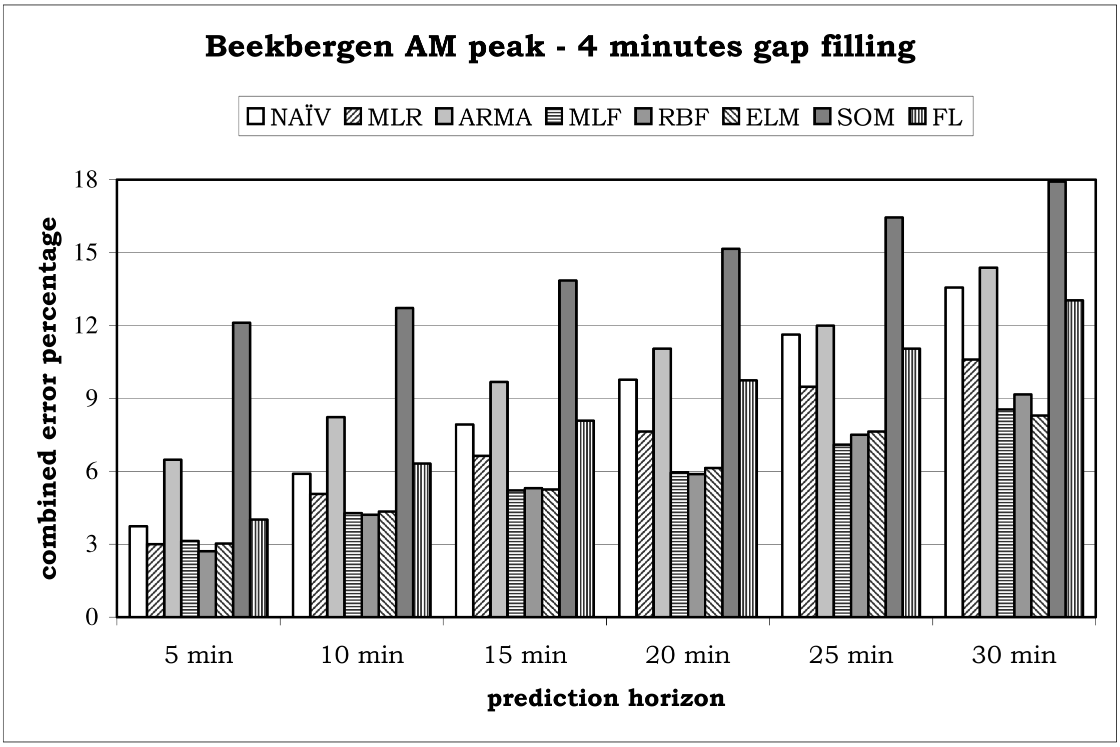

Figure 8.52: Combined results for the Beekbergen AM peak period, where 'not congested' gaps of 4-minute (or less) duration are transformed to 'congested'.

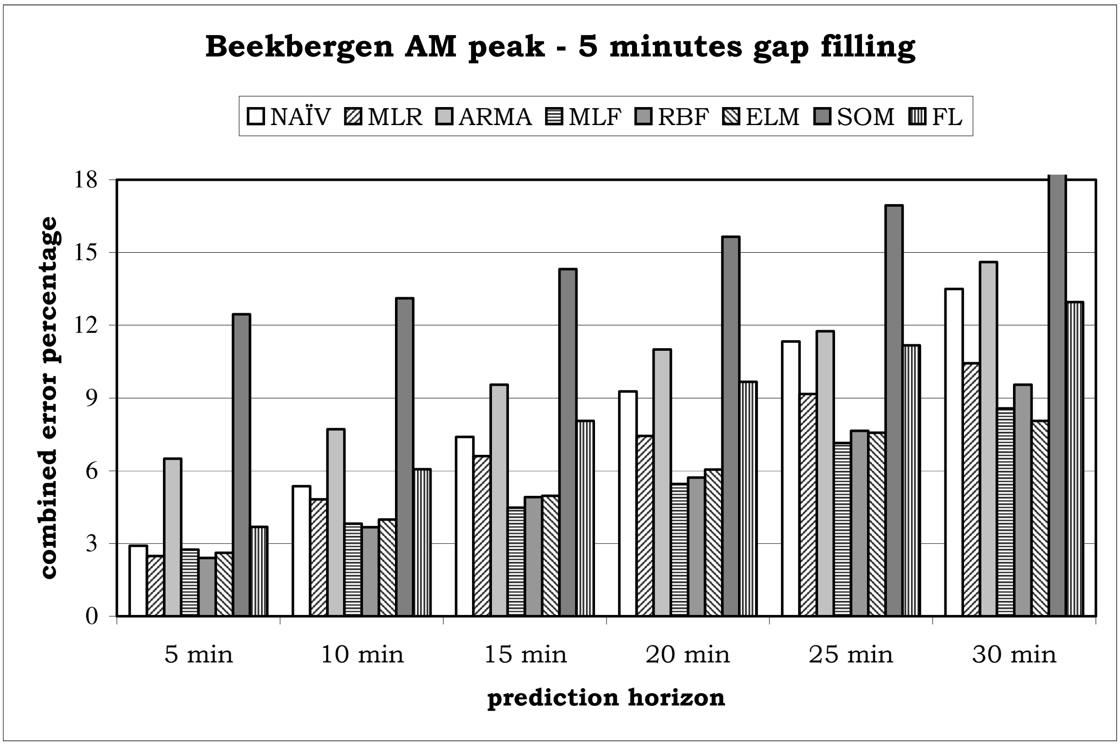

Figure 8.53: Combined results for the Beekbergen AM peak period, where 'not congested' gaps of 5-minute (or less) duration are transformed to 'congested'.

Figures 8.49 – 8.53 show that when non-congested gaps are filled, the results still share the same pattern as can be seen in figure 8.33; the results of the Beekbergen morning peak period without any non-congested gaps being filled (transformed to 'congestion'). The rank of performance of the methods is not disturbed.

However, the procedure does result in improvement for all models that are built on the Beekbergen morning peak period data, except for the SOM-based models. The results improve as the gaps that are filled are increasing. The most noteworthy relative improvements were made at the short prediction horizons, while improvements measured in percent points are more or less equally distributed over the total range.

Examination of the results of appendix K show that for the Beekbergen evening peak period, again, the results deteriorate for the SOM models. For the MLR, the supervised ANN and the FL models, the overall optimum results are found for gap fillings of 1 or 2 minutes (or less). The naïve and ARMA models show overall optimum results for gap fillings of 3 and 4 minutes, respectively.

The results of the Hoevelaken morning peak period: the MLR and RBF ANN models get their overall optimum at gap fillings of 3 and 2 minutes. For the remaining methods similar findings to the Beekbergen morning peak results are shown: SOM models suffer from increasing errors, while the bulk of the models show error decrease as the gaps filled are getting longer.

The gap filling procedure for the Hoevelaken evening peak period reveals an overall performance deterioration as the gap filling increase for all models. This is not surprising since the models tend to output 'no congestion' for almost the entire period and the gap filling procedure increases the total number of congested minutes. Therefore the output has fewer minutes that are correctly predicted.

CHAPTER 9

Conclusions

"A conclusion is the place where you got tired of thinking."

Martin H. Fischer

9.1 Introduction

The first section of this closing chapter will address the hypotheses as stated in chapter 5; they are either accepted or rejected. The second section of this chapter contains the overall conclusions and places them in context of other research. Additionally, the implications of the overall conclusions are described and directions for further research are given.

9.2 Confirmation or rejection of hypotheses

The successive hypotheses will now be assessed. The results, as described in chapter 8, are the foundation for either the confirmation or rejection of the hypotheses.

9.2.1 Hypothesis 1

> *Any method's performance will deteriorate with increasing prediction horizon. The rate of increase will alter when the prediction horizon exceeds the travel time period of the monitored section.*

As can be seen from the graphs depicted in 8.10 (figures 8.33 – 8.36) this hypothesis is confirmed for the Beekbergen morning and evening peak period and the Hoevelaken morning peak period. The Hoevelaken evening peak period is different in that the models were not built to function properly. This is due to the low congestion percentage that was reported by the target detector as already explained in 8.10.4.

Conclusion: hypothesis 1 is confirmed.

9.2.2 Hypothesis 2:

> *Due to the different (faster) congestion build-up in the morning peak compared to the evening peak, the significance of individual detectors will alter faster during the morning peak than during the evening peak and therefore the method's prediction performance of the evening peak will outperform that of the morning peak.*

This hypothesis can only be confirmed if the same location has the same target detector for the morning and evening peak period. Since this is not the case for Beekbergen and Hoevelaken a decision on whether this hypothesis is confirmed or rejected cannot be reached.

Conclusion: hypothesis 2 is neither confirmed nor rejected. Further study is needed to reach confirmation or rejection.

9.2.3 Hypothesis 3:

Feedback information from previous time steps does significantly improve the method's performance.

As explained in chapter 5; more information means less uncertainty. This could be translated to the hypothesis that State-Space (Elman) ANNs will outperform MLF ANNs while both types of models will use the same information. Since Elman ANNs use the output from time *t-1* as additional input for time *t*, the Elman ANNs have additional information on previous time steps.

The results in chapter 8 reveal that both methods perform equally well. This seems to be in contrast with Shannon's Theorem. However, Shannon did mention that the additional information only reduced uncertainty if it was not redundant with the already present information. A closer look at the input variables of the MLF ANNs used in the present study shows that they implicitly are built up of a state-space nature due to the use of input variables coming from spatial distributed detectors. This leads to the conclusion that feedback information from previous time steps is redundant, due to the information present through acquired data coming from other detectors (see figure 6.5). Hence a conclusion is reached.

Conclusion: hypothesis 3 is rejected (Restriction: the use of a detector constellation that includes upstream detectors).

9.2.4 Hypothesis 4:

Methods that are able to model non-linearity will outperform methods that use linear modelling when it comes to a non-linear phenomenon like congestion prediction.

As mentioned in chapter 5 and 7, MLF ANNs use the same information as MLR models do, the difference being that MLF ANNs use non-linear processing and thus are able to model non-linearity, while MLR uses linear processing. By comparing the performance results of the two methods hypothesis 4 can be either rejected or confirmed.

The results described in section 8.10 show that MLF ANNs and MLR models both produce good results. However, the results of MLF ANNs are better in almost every situation. The most dramatic difference can be seen in the results coming from the Hoevelaken evening peak period; the MLR models suffered from singularities and therefore the results were unreliable and had a big error. On the other hand, the results of the supervised ANNs were also useless for practical reasons (they gave 'no congestion' as output on every occasion). Still, the MLF ANNs outperformed the MLR models.

Conclusion: hypothesis 4 is confirmed.

9.2.5 Hypothesis 5:

Upstream spatial induction loop information provides more useful information for predictions than historical temporal induction loop information from the bottleneck.

This hypothesis can be checked by comparing the ARMA time series analysis performance results with those of MLR. Comparison of the results in 8.10 clearly shows that MLR models outperform the ARMA time series models.

Conclusion: hypothesis 5 is confirmed.

Hypothesis 5a states that:

MLF ANNs will outperform ARMA time series.

Since hypothesis 4 and 5 both are confirmed, this automatically leads to the confirmation of hypothesis 5a.

Conclusion: hypothesis 5a is confirmed.

9.2.6 Hypothesis 6:

The method(s) that perform best at predicting recurrent congestion are the same as those that give the best performances at predicting non-recurrent congestion.

The results described in section 8.10 reveal that the supervised ANNs produce the best performances with respect to recurrent congestion prediction. However, non-recurrent congestion was not registered within the acquisition period, i.e. the month May of 2001. Hence it is not possible to confirm this hypothesis, nor is it possible to reject it.

Conclusion: hypothesis 6 is neither confirmed nor rejected. Further study is needed to reach confirmation or rejection.

9.2.7 Hypothesis 7:

The parameters / weights of models will alter with changing prediction horizons.

The results of the sensitivity analysis (8.11) immediately show that the parameters (of the MLR models) and the weights (of the MLF ANNs) change throughout the process of prediction horizon alteration. The main pattern that can be seen is: at the 0-minute prediction horizon information acquired through the target detector and detectors immediately in the vicinity of the target detectors are most significant. The significance then quickly deteriorates as the prediction horizon increases. Additionally, the significance of loop detectors that are positioned upstream of the target detector first increases, after which it decreases.

Conclusion: hypothesis 7 is confirmed.

9.2.8 Hypothesis 8:

Due to the presence of heavy traffic, congestion will occur while traffic intensities are substantially below traffic congestion intensities in the absence of heavy traffic. Effectively, capacity will deteriorate.

If hypothesis 8 were true it would mean that the variables belonging to heavy traffic (intensity, mean speed and standard deviation of mean speed; numbers 8 – 10) would be of considerable significance. Since section 8.11 did not reveal such significance for heavy traffic, this hypothesis cannot be confirmed. However, throughout the entire research period, no high percentages of heavy traffic were reported. Therefore, it also is not possible to reject hypothesis 8.

Conclusion: hypothesis 8 is neither confirmed nor rejected. Further study is needed to reach confirmation or rejection.

9.3 Overall conclusions

This section first describes the overall conclusions of this study, followed by a contextual positioning of the conclusions. Subsequently, implications of the conclusions are given. The section closes with directions for further research.

9.3.1 This study

SOM models, FL models and ARMA models are equally as good as or were outperformed by the naïve models, meaning that these models do not have added value under the data acquisition circumstances, as described in chapter 6, and should therefore not be considered as congestion prediction tools.

How is it possible that promising methods such as time series analysis and fuzzy logic (as can be derived from chapter 2) are outperformed by the naïve method? To explain this, the input variables used by the models should be looked at more in-depth and comparison of their nature should be made. All models based upon time series analysis and fuzzy logic use data gathered by the target detector only as input variables. Similarly, so do the naïve models. However, both the time series models as well as the fuzzy logic models use traffic flow, mean speed, and standard deviation of mean speed of three vehicle length classes plus occupancy as input variables, while the congestion indicator is used as input variable for the naïve models. The task at hand for the models can be made clear as follows: Imagine an (not necessarily orthogonal) eleven-dimensional space, all dimensions based on the aforementioned input variables. Congestion prediction for the time series analysis method and the fuzzy logic method is then simulated by the function mapping of a point in ten-dimensional space onto either of two separated points of the remaining one-dimensional line (the points representing ‘congestion’ and ‘no congestion’). Congestion prediction for the naïve method is simulated using the stationary function: ‘congestion’ (on the one-dimensional line) stays ‘congestion’ and ‘no congestion’ stays ‘no congestion’. Under stationary traffic conditions the task for the naïve models is trivial. However, for the time series analysis models and the fuzzy logic models this task is more complicated; this can also be seen given the errors that these models produce during the 0-minute prediction horizon. Therefore, the information present in the data for the ten input variables is insufficient for the models to reliably determine whether traffic will suffer from ‘congestion’ or ‘no congestion’, even in the present situation.

The supervised ANN models show the best results and when their mutual scores are compared little difference can be seen. These methods are clearly the best choice when it comes to congestion prediction. In fact, although they have no information regarding the state of the congestion indicator at present time, they still substantially outperform the naïve models. Therefore, the information present in the data for all input variables is sufficient for the models to determine more reliably than the naïve models whether traffic will suffer from ‘congestion’ or ‘no congestion’ in the future.

It is noteworthy that MLR models have occupancy and intensities of the shortest vehicle class as their most significant variables, while for the supervised ANNs the most important variables are mean speed of all, but at least of the shortest, vehicle classes. Apparently, non-linear methods use the information that is stored in mean speed data, while linear models are better served by information stored in occupancy and intensity.

The results of the MLR and the supervised ANN models do not differ very much. Although the results of the ANN models generally are better than those of the MLR models, the difference is small. This finding indicates that the mapping of the acquired traffic variables onto the congestion prediction indicator is not described by a strong non-linear function. However, the theoretical necessary conditions for the application of MLR do not hold. These are:

1. Independent variables should be mutually independent of each other;
2. There is a linear relationship between dependent and independent variables;
3. The residuals (the errors between the real observed value and the MLR value) should have a normal distribution and should be uncorrelated with the independent variables.

These conditions were not met in this study. They also explain the difficulties that the models had with congestion prediction during the Hoevelaken evening peak period; the transverse function possessed singularity.

Not so remarkable findings, but nonetheless important ones, have to do with upstream detectors and the choice of the target detector. In order to get good predictions, one has to have several upstream detectors for quite a stretch at one’s disposal. Also, the bottleneck detector (target detector, i.e. the first detector to report congestion) needs to suffer from congestion for at least more than 10% of the time or should not suffer from stop-and-go congestion. If both criteria are violated the results will most likely show resemblance with the ones found at the Hoevelaken evening peak period as described in this chapter.

The findings on the optimum aggregation level by making use of the congestion gap filling procedure are not straightforward. Perhaps the way congestion occurs is of influence (stop-and-go congestion versus longer periods of congestion), maybe the procedure is not valid enough. However, the data that was present at this study cannot be transformed easily into other aggregation levels, especially if one considers the standard deviation from the mean speed. If one wants to examine the optimum aggregation level, one needs individual vehicle data to build several distinctive aggregation level data sets, develop models on those data sets and then compare results.

9.3.2 Context of the overall conclusions

How do the overall conclusions relate to findings of other studies? Although there is virtually no previous work on traffic congestion prediction, the conclusions of this study correspond with results found in studies on traffic flow prediction, travel time prediction and incident detection.

When the results of traffic flow prediction studies are examined, similar results in method performances are found, i.e. the non-linear models show the best performances. However, results of time series analysis models in traffic flow prediction studies tend to lie closer to those of linear models than the gap that is reported in this study. This can be explained by the assumption that the process of traffic flow prediction is more linear than the prediction of congestion, more so since the majority of the models used for traffic flow prediction consist of traffic flow as input variable and traffic flow as output variable.

Similarly, analysis of results of travel time prediction studies shows that non-linear data driven models, especially ANN models, outperform models based on other methods. The advantage that ANN models have over other models is most evident during phases when traffic congestion is building up and breaking down.

The same holds for incident detection research. The methods that are able to model non-linearity seem to outperform linear models with respect to incident detection, again similar to models that predict traffic congestion. Another similarity lies in the conclusion that linear state-space models seem to produce acceptable incident detection results, while multi linear regression models also produce acceptable traffic congestion prediction outcomes (under certain circumstances). Hence, the reported conclusions can be translated to traffic congestion prediction.

9.3.3 Implications of the overall conclusions

Traffic congestion is a non-linear phenomenon. Prediction of traffic congestion is not always straightforward and has to fulfil certain requirements. In the Netherlands, traffic management is taking steps to further maturity by using predefined scenarios for the engagement of traffic management measures (Dutch Directorate for Public Works and Water Management, 2002). However, the impact of the foreseen traffic management measures are usually based models that do not incorporate the non-linearity of hysteresis that influences the dynamics of traffic congestion. Reliable traffic congestion prediction models have additional value in the process of scenario development.

Most Commercial Off The Shelf (COTS) dynamic traffic models use simplified *k-q* diagrams (see figure 1.4 in chapter 1) to model congestion and quantify hours lost due to congestion. The findings of this research show that the modelling of congestion is a location dependent non-linear phenomenon with a dynamic nature (hysteresis). This implies that the outcomes of COTS dynamic traffic models have to be regarded with scepticism. This is especially the case when the results are used to support high impact policy related choices (being their primary objective of use), e.g. the construction or expansion of a road.

9.3.4 Further research

In section 9.2 directions for further research were already identified. The first subject is the research of model performance under different speed of traffic congestion building-up and breaking down during the morning peak and the evening peak. It was hypothesised that the significance of individual detectors will alter faster during the morning peak than during the evening peak and therefore the method's prediction performance of the evening peak will outperform that of the morning peak.

The second identified research subject deals with non-recurrent congestion. The question was posed if the results of the models based on the methods described in this research would show a similar pattern if non-recurrent congestion was the subject of research.

The last research subject direction in 9.2 has to do with the influence of heavy traffic on the model performance. Since it is anticipated that heavy traffic will increase significantly, i.e. 40 – 80% in the period to 2020; see Ministry of Transport, Public Works and Water Management (2005), it would be interesting to find out how this will influence the performances of traffic congestion prediction models.

Based on the research of Click *et al.* (1997) assumptions were made that 1-minute time bins are the optimal aggregation level for input data that feed congestion prediction models. Therefore, the determination of the optimum aggregation level of input data was not the objective of this study, although efforts were made by using the congestion gap filling procedure to mimic other aggregation levels. A study that uses individual vehicle data to build several distinctive aggregation level data sets, develop models on those data sets and then compare results is a direction of further research to find the optimum aggregation level of input data.

Another research issue concerns the reliability of the models in the present of unreliable detector data. In this research, unreliable data were substituted with the last known reliable values, but it is necessary to gain additional knowledge on the robustness of the models with respect to missing or corrupt input data. Good examples of such assessments can be found in e.g. Van Lint (2004) and Van Lint *et al.* (2005).

A final subject for further research concerns the inclusion of weather conditions into the models. Although this information initially seems largely redundant, given the fact that detector data implicitly incorporates human driving behaviour under changing weather conditions, it may be interesting to find out if this statement holds or that separate environmental circumstances will improve the performance of the models.

R

References

"The only source of knowledge is experience."

Albert Einstein

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APPENDIX A

A short history of DTM

A.1 Europe

In 1985 the EUropean REsearch Coordination Agency (EUREKA) project, an open framework for co-operation between European industry and research institutions, was established by the EC. This resulted amongst others in 1986 in the PROgraM for European Traffic with Highest Efficiency and Unprecedented Safety (PROMETHEUS), which was initiated by European car manufacturers and its first objective was to aim at in-car technological innovations. It contained many projects divided into four functional areas:

- Improved Driver Information (e.g. obstacle detection);
- Active Driver Support (e.g. safety margin determination);
- Co-operative Driving (e.g. intelligent cruise control);
- Traffic/Fleet Management (e.g. trip planning).

Three years later, in 1988, the EC launched the above-mentioned DRIVE program. The objectives of the DRIVE I program were to increase road transport efficiency, safety and decrease environmental pollution due to road traffic within the EC by the application of Road Transport Informatics (RTI) and telecommunications. DRIVE I was split into three subdivisions:

- RTI technologies;
- Evaluation of strategic options;
- Specification, protocols and standardisation proposals.

The approach of the DRIVE program was to find an optimal path for pre-selected RTI technologies and systems and then to focus support on implementation in those domains where public needs and benefits have been identified.

In 1991, the sequel (DRIVE II) was started and its objectives were to contribute to the development, in the field of transport, of integrated trans-European services using advanced Information Technology (IT) and communications to improve the performance (safety and efficiency) of passenger and goods transport services, and at the same time reduce the impact of transport on the environment. DRIVE II was also split into 3 subdivisions:

- Strategies for the use of technologies, telematic services and systems;
- Technologies and experimental development of systems;
- Validation and pilot projects.

Seven interrelated areas of major operational interest cover these main subdivisions:

  - Demand management: Use of technology in helping urban authorities and the managers of inter-urban transport to strike an efficient balance between travellers' demands and preferences and the capacity of the road and rail network;

- Traffic and traffic information systems: Collection, processing and distribution of travel and traffic information of direct use to people at home, in the office and in the course of a journey;
- Integrated urban traffic management systems: Improvement and integration of transport systems used in cities;
- Integrated inter-urban traffic management systems: Systems for traffic control and driver information on motorways and parallel roads;
- Driver assistance and co-operative driving: Systems to assist the driver and to communicate information between vehicles;
- Freight and fleet management: Freight and logistic management systems enabling inter-modal operations;
- Public transport management: Implementation and testing of an integral vehicle scheduling and control system for inter-urban and rural public transport applications.

While DRIVE I focused on "exploring the options", the aim of DRIVE II was to "prepare for implementation". In 1995 the DRIVE III program has gone operational under the name European Road Transport Telematics Implementation Co-ordination Organisation (ERTICO), which actually acts as an umbrella for DRIVE and PROMOTHEUS, and which' main target is to "implement large scale pilots".

Currently, the FRAME and the Trans-European Network for Transport (TEN-T) programs receive a lot of attention. The former program is directed towards the implementation and enhancement of the European ITS Framework Architecture, whereas the latter is directed towards implementation of ITS related research. This program, paid for by the European Union, started in 1983 and is worth around 500 Million Euro annually during the last 5 years.

A.2 America

In the late 1980's the need for a formal organisation became apparent and Intelligent Vehicle Highway Systems (IVHS) America was formed in 1990 to act as a Federal Advisory Committee for the US Department of Transportation. In December 1991, the Inter-modal Surface Transportation Efficiency Act (ISTEA) became law. Its purpose is to develop "a national inter-modal transport system that is economically sound, to provide the foundation for the nation to compete in the global economy, and to move people and goods in an energy-efficient manner". In June 1992 IVHS America produced a 'Strategic Plan for Intelligent Vehicle Highway Systems in the US'. This plan was also split in three subdivisions:

- a national system that operates consistently and efficiently across the U.S.A. to promote the safe, orderly and expeditious movement of people and goods;
- an efficient mass transit system that interacts smoothly with improved highway operations;
- a vigorous U.S.A. IVHS industry supplying both domestic and international needs.

In 1994 the IVHS program was renamed into Intelligent Transportation Systems (ITS) indicating that besides car traffic also other modes of transport need attention. Analogous to DRIVE, there are six interrelated areas of major operational interest that cover these main subdivisions:

- Advanced Traffic Management Systems (ATMS): ATMS is expected to integrate management of various roadway functions, predict traffic congestion and provide alternative routing instructions to vehicles and transit operators. Real time data will be collected, utilised and disseminated. Dynamic traffic control systems will respond in real time to changing conditions. Incident detection is seen as a critical function in this area;
- Advanced Traveller Information Systems (ATIS): ATIS involves providing data to travellers in their vehicle, in their home, or at their place at work. Information will include: location of incidents, weather problems, road conditions, optimal routing, lane restrictions, and in-vehicle signing. The information will be provided to both vehicle drivers and transit users;
- Advanced Vehicle Control Systems (AVCS): AVCS is viewed as an enhancement of the driver's control of the vehicle to make travel safer and more efficient. Systems range from cruise control and collision warning to completely automatically controlled vehicles in special lanes. Huge improvements in highway capacity are possible by assuming partial or total control of vehicles;
- Commercial Vehicle Operations (CVO): Private operators of trucks, vans and taxis are adopting ITS technologies to improve the productivity of their fleets and the efficiency of their operations. Faster dispatching, efficient routing (just-in-time principle), and more timely pick-ups and deliveries are possible. Safety improvements are possible by tracking hazardous material transports, and monitoring driver fatigue;
- Advanced Public Transport Systems (APTS): APTS involves providing information to transit users concerning information on routes, schedules, delays and fares. The scheduling of public transport vehicles and the utilisation of bus fleets can be improved by utilising real time information. Another example is an automated fare collection system;
- Advanced Rural Transportation Systems (ARTS): The special economic constraints of relatively low-density roads and the question of how ITS technologies can be applied in this

environment is a challenge that has been undertaken by many rural states. The main focus is on highway safety. Other objectives are to provide in-vehicle route information, traffic and weather advisory information and the use of beacons to locate accidents or disabled vehicles in remote areas.

When both the efforts of Europe and the U.S.A. are compared it is apparent that ITS America has invested in an enormous amount of projects that outstrip the European ERTIGO programmes. What strikes is that the U.S.A. program lacks an interest in Demand Management.

Since June 1997, ITS Canada was incorporated out of the forerunner ITS Roundtable of the Transportation Association of Canada, a small but dedicated group of ITS professionals that had operated since the early 1990s under the aegis of the Association's Research and Development Council.

A.3 Japan

Uncoordinated efforts of ITS in Japan can be traced back to the early 1970's. This led to a diversity of applications by various industrial and governmental institutions that are not able to co-operate with each other but are merely competitive. The Ministry of International Trade and Industry (MITI), for example, funded in 1973 the Comprehensive Automobile Control System (CACS) whereas funding of the Ministry of Construction (MOC) and the governmental Highway Industry Development Organisation (HIDO) in 1984 led to the Road/Automobile Communication Systems (RACS). Also in 1984 the Ministry of Post and Telecommunications (MPT) started the Advanced Traffic Information and Communication System (AMTICS). In the early 1990's the need for national co-ordination and standardisation was recognised and consequently RACS and AMTICS merged into the Vehicle Information and Communication System (VICS). Comprehensive programs such as Advanced Traffic Information Services (ATIS), Advanced Road Traffic Systems (ARTS), and Super Smart Vehicle System (SSVS) originated. In order to integrate the international works in the field of transport telematics the VEhicle, Road and Traffic Intelligence Society (VERTIS) was established in 1994. VERTIS has been renamed ITS Japan since June 2001.

APPENDIX

B

Monitoring

There are several techniques and sensors available to monitor the current state of the transport system. Monitor sensors are often described in textbooks on ITS, such as Zhao (1997), McQueen and McQueen (1999), Sussman (2000), Klein (2001), and McQueen *et al.* (2002).

Historically, manual counting is the method that dates back the furthest and is still in use today. Its use is mainly restricted to studies at locations that are difficult to monitor by other methods and where the monitoring time frame is relatively short due to the high personnel costs that this method generates.

The most widely used option is to monitor traffic by means of (dual) induction loops. Due to its maturity this technology gives no surprises. It can be used to provide traffic parameters as presence, intensity, occupancy, and speed. When disaggregated data is acquired on individual vehicle level it is also possible to extract information about headways and gaps.

Pneumatic tube counters are also widely used for temporary studies. They can be used for registration of intensities but also as speed traps if two tube counters are used in parallel. Because of their mobile character they are predominantly used to check if certain road sections are unsafe (see e.g. Barbosa *et al.*, 2000; Pau and Angius, 2001; Várhelyi *et al.*, 2003), if road sections are environmental unhealthy (see e.g. Namdeo *et al.*, 1999; Diesendorf, 2000; Tsai *et al.*, 2002; Tsai *et al.*, 2004) or have inadequate capacity (see e.g. Chen and Bell, 2002; Hjälmdahl and Várhelyi, 2004).

Another option to monitor traffic is by means of cameras. Vehicle detection can be performed by using a simple image detection approach which is called the background differencing technique, based on a pixel by pixel comparison (Dickinson and Waterfall, 1984a,b; Fathy and Siyal, 1995b; Matthews *et al.*, 1996; Taktak *et al.*, 1996; Bertozzi *et al.*, 1997) or more complex image detection using morphing (Li *et al.*, 2002) or a combination of morphing and edge detection (Fathy and Siyal, 1995a). It is used to estimate the intensity, speed, and occupancy of vehicles per time frame. The roots of vehicle detection can be found in linear correlation, or matched, filters for automated pattern (or target) recognition (Hester and Casasent, 1980; Arsenault and Hsu, 1982; Casasent, 1984; Kallman, 1986). Since artificial neural networks (ANN's) have an excellent record with respect to pattern recognition, ANN's are also extensively used for vehicle detection and identification purposes (Bullock *et al.*, 1993; Gader *et al.*, 1995; Mantry and Bullock, 1995; Jouseau and Dorizzi, 1999).

Microwave radar is a technique that also can be used to detect vehicles. Microwaves with a frequency ranging from 1 to 30 GHz are transmitted and used as either a Continuous Wave (CW) Doppler radar or as a Frequency Modulated Continuous Wave (FMCW) radar. Both radars are predominantly used to measure (individual) vehicle speed and are insensitive to inclement weather, however, the CW Doppler radar is unable to detect stopped vehicles (Manor, 1996; Gribbon, 1998; Harlow and Peng, 2001) since there is no difference in emitted and received wave frequencies; to get more familiarised with the Doppler principle have a look in any physics textbook on waves, such as Pain (1993).

Range sensors based on Laser (Harlow and Peng, 2001) have also recently seen the light. Applications typically involve height detection of trucks, e.g. before entering a tunnel thus protecting the construction of that tunnel (and the truck).

Infrared sensors (Klein, 1997; Ogasawara *et al.*, 1999) are another class of wave-based sensors. We can distinguish between active infrared Laser sensors and passive infrared Laser sensors. Active sensors consist of infrared beam transmitting optics and receiving optics. The scanning beams are directed towards the lanes and when vehicles pass these beams the receiving optics register a time difference that can be converted to vehicle speed (Schwartz, 1994 and 1996). Passive infrared sensors contain energy-sensitive elements that collect energy from a scene in their focal plane. When energy fields are detected that are different from the background energy they are transformed into pixels thus providing images of objects of dissimilar energy (read: temperature) levels.

Ultrasonic sensors (Kumagai *et al.*, 1992) transmit waves within the 25 kHz to 50 kHz frequency domain; just above the human audible range. It also uses the Doppler principle by transforming the frequency shift in emitted and received wave pulses of the scanning directions into object speeds, vehicles count, lane occupancy and presence.

Yet another wave-based sensor is the acoustic radar. This radar's working field is in the 20 – 15000 Hz range; i.e. the same frequency domain as the human ear is capable to process, hence the term 'acoustic'. It processes the audible sounds that are produced by vehicles and thus measures vehicle passage, presence, and speed (Nooralahiyan *et al.*, 1997, 1998). Since they do not emit waves, these sensors are passive and operate in a fashion comparable to that of passive infrared sensors.

Finally, there is the class of magnetic sensors. These sensors are passive devices that detect perturbations of the earth's magnetic field created by a metal object when this object enters the magnetometer's detection zone (Sampey, 1994; Jousea and Dorizzi, 1999). There are two types of magnetic field sensors that are used for traffic flow measurements. The first type is the two-axis fluxgate magnetometer, containing a primary winding and a secondary sense winding on a bobbin surrounding a soft magnetic material core perpendicular to the first one. When a vehicle enters the detection zone the secondary winding generates an electronic current that is maintained until the vehicle leaves the detection zone. The second type is the magnetic detector or induction coil magnetometer. It detects the vehicle signature by measuring the distortion in the magnetic flux line induced by the change in the earth's magnetic field produced by a moving ferrous metal object. It does so because the single coil winding on a magnetic core generates an electric current whenever ferromagnetic objects perturb the magnetic field. In order to do so it is necessary that the object moves, so this type of magnetic sensor is unable to detect stopped vehicles, contrary to the two-axis fluxgate magnetometer. To get more familiarised with these electromagnetic principles have a look in any physics textbook on electromagnetism, such as Purcell (1985).

APPENDIX C

ARMA parameter estimation

C.1 ARMA time series

As seen in section 3.4, equation (3.7), we can mathematically write an ARMA(p,q) time series as:

$$X_t = \mu + a_1 X_{t-1} + a_2 X_{t-2} + \ldots + a_p X_{t-p} + b_0\varepsilon_t + b_1\varepsilon_{t-1} + \ldots + b_q\varepsilon_{t-q} \tag{C.1}$$

for $t = p$, $p + 1$, … and with ε_t is white noise with mean zero and variance σ^2. Without loss of generality we may take $b_0 = 1$ if needed. Also, processes are often centred so that we can put $\mu = 0$. The parameters μ, a_1, a_2, …, a_p, b_0, b_1, …, b_q, and σ^2 are to be estimated on the basis of observations of X_0, X_1, …, X_{F-1}. The orders p and q are assumed to be known.

C.2 Least squares estimators

The values of X_p, X_{p+1}, …, X_{F-1} are generated by initial conditions X_0, X_1, …, X_{p-1} and by ε_{p-q}, ε_{p-q+1}, …, ε_{F-1} . Define the vectors (see also eq. 3.8):

$$X = \begin{bmatrix} X_p \\ X_{p+1} \\ \cdots \\ X_{F-1} \end{bmatrix}, \quad X^0 = \begin{bmatrix} X_0 \\ X_1 \\ \cdots \\ X_{p-1} \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_{p-q} \\ \varepsilon_{p-q+1} \\ \cdots \\ \varepsilon_{F-1} \end{bmatrix} \tag{C.2}$$

Then we have

$$\underbrace{\begin{bmatrix} 1 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ -a_1 & 1 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ -a_2 & -a_1 & 1 & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & \cdots & \cdots & \cdots & 0 & -a_p & \cdots & -a_1 & 1 \end{bmatrix}}_{R} X$$

$$= \underbrace{\begin{bmatrix} b_q & b_{q-1} & \cdots & \cdots & b_0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & b_q & \cdots & \cdots & b_1 & b_0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & 0 & b_q & \cdots & \cdots & b_1 & b_0 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 & b_q & \cdots & b_1 & b_0 \end{bmatrix}}_{M} \varepsilon$$

$$+\underbrace{\begin{bmatrix} a_p & a_{p-1} & \cdots & \cdots & a_1 \\ 0 & a_p & \cdots & \cdots & a_2 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & \cdots & \cdots & \cdots & 0 \end{bmatrix}}_{P} X^0 \quad + \underbrace{\begin{bmatrix} 1 \\ 1 \\ \cdots \\ 1 \end{bmatrix}}_{e} \mu \qquad \text{(C.3)}$$

The expression (see also eq. 3.8)

$$RX = M\varepsilon + PX^0 + \mu e \qquad \text{(C.4)}$$

is more compact. R is square with dimensions (F – p) × (F – p). M has dimensions (F – p) × (F – p + q), and P has dimensions (F – p) × p. M generally is not invertible, so that (C.4) is not uniquely solvable for ε. The least squares solution for ε is

$$\hat{\varepsilon} = M^T\left(MM^T\right)^{-1}\left(RX - PX^0 - \mu e\right) \qquad \text{(C.5)}$$

This yields the sum of squares

$$\left(\hat{\varepsilon}\right)^T\hat{\varepsilon} = \left(RX - PX^0 - \mu\right)^T\left(MM^T\right)^{-1}\left(RX - PX^0 - \mu e\right) \qquad \text{(C.6)}$$

Minimisation with respect to the parameters μ, a_1, a_2, …, a_p, b_0, b_1, …, b_q that occur in the coefficient matrices R, M and P yields the desired estimators. After computing the residuals with the help of (C.5) the variance σ^2 may be estimated as the sample average of the squares of the residual.

C.3 Maximum likelihood estimation

After the preparations of C.2 the determination of the maximum likelihood estimator is rather straightforward. We use the normal probability density of X given X^0. We rewrite (C.4) to

$$X = R^{-1}\left(M\varepsilon + PX^0 + \mu e\right) \qquad \text{(C.7)}$$

and inspection of (C.7) reveals that the conditional expectation of X given $X^0 = x^0$ equals $R^{-1}(Px^0 + \mu e)$. The accompanying conditional variance matrix is $\sigma^2 R^{-1}MM^T(R^{-1})^T$.

According to elementary probability theory the joint normal probability density function of independent stochastic variables X_0, X_1, …, X_{F-1}, each with a standard normal distribution, is

$$f_X(x) = \prod_{j=1}^{n} f_{X_j}(x_j) = \prod_{j=1}^{n} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x_j^2} = \frac{1}{\left(\sqrt{2\pi}\right)^n} e^{-\frac{1}{2}\sum_{j=1}^{n} x_j^2} = \frac{1}{\left(\sqrt{2\pi}\right)^n} e^{-\frac{1}{2}x^T x} \tag{C.8}$$

where x represents the column vector with components x_1, x_2, …, x_n.

Now let X be a vector-valued stochastic variable of dimension M with joint probability density function $f_X(x)$. Furthermore, define the stochastic variable $Y = g(X)$ and let $g : \mathbf{R}^N \rightarrow \mathbf{R}^N$ be a differentiable bijective map with inverse g^{-1}. Then Y has the joint probability density function

$$f_Y(y) = f_X\left(g^{-1}(y)\right) \cdot \left|\det J(y)\right| \tag{C.9}$$

J is the Jacobian matrix of $h = g^{-1}$. The entry J_{ij} of the $N \times N$ matrix J is given by

$$J_{ij}(y) = \frac{\partial h_i(y)}{\partial y_j}(y) \tag{C.10}$$

Combining (C.7), (C.8) and (C.9) with the fact that det R = 1 we get

$$f_{X|X^0}\left(x|x^0\right) = \frac{1}{\left(\sigma\sqrt{2\pi}\right)^{F-p}\sqrt{\det MM^T}} e^{-\frac{1}{2\sigma^2}\left(Rx-Px^0-\mu e\right)^T\left(MM^T\right)^{-1}\left(Rx-Px^0-\mu e\right)} \tag{C.11}$$

The log likelihood function thus is

$$\begin{aligned} L = \quad & -(F-p)\ln\left(\sigma\sqrt{2\pi}\right) - \frac{1}{2}\ln\det MM^T \\ & -\frac{1}{2\sigma^2}\left(RX - PX^0 - \mu e\right)^T\left(MM^T\right)^{-1}\left(RX - PX^0 - \mu e\right) \end{aligned} \tag{C.12}$$

Here we have replaced x with X and x^0 with X^0. Again we recognise the sum of squares $(RX - PX^0 - \mu e)^T(MM^T)^{-1}(RX - PX^0 - \mu e)$. With the definitions

$$Q \equiv \begin{bmatrix} -P & R \end{bmatrix}, \quad Z \equiv \begin{bmatrix} X^0 \\ X \end{bmatrix} \tag{C.13}$$

we may represent the sum of squares in the more compact form

$$(QZ - \mu e)^T \left(MM^T\right)^{-1} (QZ - \mu e) \tag{C.14}$$

Least squares estimation involves minimisation of (C.14), maximum likelihood estimation maximisation of (C.12).

APPENDIX D

Detector availability

Detector availability, April 2001 – August 2001

Monthly availability report, Version 1.0
Availability in %

Observation point (BPS-attributes)	Type	apr '01	may '01	jun '01	jul '01	aug '01
RW 1 104.2 85 1 HR R S 1 R- R	RSW	99	99	97	97	98
RW 1 104.2 85 1 HR R S 2 R- R	RSW	99	99	97	97	97
RW 1 104.2 95 0 VW d - S 1 R- L	RSW	99	99	97	97	98
RW 1 104.9 90 0 VW a - S 1 R- R	RSW	99	99	97	97	98
RW 1 105.0 70 1 HR L S 1 R- L	RSW	90	97	95	97	98
RW 1 105.0 70 1 HR L S 2 R- L	RSW	91	99	97	97	98
RW 1 105.0 80 1 HR R S 1 R- R	RSW	99	99	97	97	98
RW 1 105.0 80 1 HR R S 2 R- R	RSW	99	99	97	97	97
RW 1 105.0 95 0 VW c - S 1 R- L	RSW	99	99	97	97	98
RW 1 105.1 40 0 VW b - S 1 R- R	RSW	99	99	97	97	98
RW 1 106.0 45 1 HR L S 1 R- L	RSW	99	99	96	97	97
RW 1 106.0 45 1 HR L S 2 R- L	RSW	99	99	97	97	97
RW 1 106.0 55 1 HR R S 1 R- R	RSW	99	99	97	97	97
RW 1 106.0 55 1 HR R S 2 R- R	RSW	99	99	97	97	97
RW 1 107.0 75 1 HR L S 1 R- L	RSW	99	99	96	97	98
RW 1 107.0 75 1 HR L S 2 R- L	RSW	99	99	97	97	98
RW 1 107.0 85 1 HR R S 1 R- R	RSW	99	99	97	97	98
RW 1 107.0 85 1 HR R S 2 R- R	RSW	99	99	97	97	98
RW 1 107.6 75 1 HR R S 1 R- R	RSW	99	99	97	97	98
RW 1 107.6 75 1 HR R S 2 R- R	RSW	99	99	97	97	98
RW 1 108.0 85 1 HR L S 1 R- L	RSW	99	99	96	97	98
RW 1 108.0 85 1 HR L S 2 R- L	RSW	99	99	97	97	98
RW 1 44.2 50 0 VW e - S 1 R- R	RSW	99	99	99	97	98
RW 1 44.2 50 0 VW e - S 2 R- R	RSW	99	99	99	97	98
RW 1 44.2 50 0 VW m - S 1 R- R	RSW	39	97	99	97	97
RW 1 44.2 50 0 VW m - S 2 R- R	RSW	39	97	99	97	97
RW 1 44.3 50 0 VW n - S 1 R- L	RSW	44	95	93	86	97
RW 1 44.3 50 0 VW n - S 2 R- L	RSW	44	95	93	86	97
RW 1 44.4 0 0 VW k - S 1 R- L	RSW	98	96	93	86	97
RW 1 44.4 0 0 VW k - S 2 R- L	RSW					
RW 1 44.4 10 0 VW f - S 1 R- L	RSW					
RW 1 44.5 85 1 HR R S 1 R- R	RSW	84	98	99	97	98
RW 1 44.5 85 1 HR R S 2 R- R	RSW	84	96	99	97	97
RW 1 44.6 35 1 HR L S 1 R- L	RSW	98	96	93	86	97
RW 1 44.6 35 1 HR L S 2 R- L	RSW	98	96	93	86	97
RW 1 44.7 25 0 VW j - S 1 R- R	RSW	0	0	0	82	97
RW 1 44.8 50 0 VW m - S 1 R- R	RSW	38	97	99	97	97
RW 1 44.8 50 0 VW m - S 2 R- R	RSW	38	97	99	97	97
RW 1 44.9 0 0 VW f - S 1 R- L	RSW	99	99	85	0	0
RW 1 44.9 0 0 VW f - S 2 R- L	RSW	99	99	85	0	0
RW 1 44.9 0 0 VW n - S 1 R- L	RSW					
RW 1 44.9 0 0 VW n - S 2 R- L	RSW					
RW 1 45.4 15 0 VW a - S 1 R- R	RSW	95	98	99	97	97
RW 1 45.4 50 0 VW m - S 1 R- R	RSW	95	98	99	97	97
RW 1 45.4 50 0 VW m - S 2 R- R	RSW	97	98	99	97	97
RW 1 45.4 85 0 VW n - S 1 R- L	RSW	94	97	85	0	0
RW 1 45.4 85 0 VW n - S 2 R- L	RSW	95	97	85	0	0

RW 1 45.4 90 0 VW d - S 1 R- L	RSW			0		
RW 1 46.4 35 1 HR R S 1 R- R	RSW	99	98	85	0	0
RW 1 46.4 35 1 HR R S 2 R- R	RSW	99	96	85	0	0
RW 1 46.9 45 1 HR L S 1 R- L	RSW	97	99	77	0	0
RW 1 46.9 45 1 HR L S 2 R- L	RSW	96	98	77	0	0
RW 1 49.2 85 1 HR L S 1 R- L	RSW	99	99	85	0	0
RW 1 49.2 85 1 HR L S 2 R- L	RSW	99	99	85	0	0
RW 1 49.2 95 1 HR R S 1 R- R	RSW	99	99	85	0	0
RW 1 49.2 95 1 HR R S 2 R- R	RSW	99	99	85	0	0
RW 1 83.4 70 1 HR L S 1 R- L	RSW	99	99	97	97	98
RW 1 83.4 70 1 HR L S 2 R- L	RSW	99	99	97	97	98
RW 1 83.4 70 1 HR R S 1 R- R	RSW					
RW 1 83.4 70 1 HR R S 2 R- R	RSW					
RW 1 84.0 95 1 HR L S 1 R- L	RSW	99	99	97	97	98
RW 1 84.0 95 1 HR L S 2 R- L	RSW	99	99	97	97	98
RW 1 84.1 5 1 HR R S 1 R- R	RSW	99	99	96	97	98
RW 1 84.1 5 1 HR R S 2 R- R	RSW	99	99	95	97	98
RW 1 84.6 15 1 HR R S 1 R- R	RSW	99	99	96	97	98
RW 1 84.6 15 1 HR R S 2 R- R	RSW	99	99	82	97	98
RW 1 85.1 15 1 HR L S 1 R- L	RSW	99	99	97	97	98
RW 1 85.1 15 1 HR L S 2 R- L	RSW	99	99	97	97	98
RW 1 87.3 10 1 HR L S 1 R- L	RSW	99	99	96	97	98
RW 1 87.3 10 1 HR L S 2 R- L	RSW	98	99	96	97	98
RW 1 87.3 20 0 VW m - S 1 R- R	RSW	90	74	81	86	79
RW 1 87.3 20 1 HR R S 1 R- R	RSW	99	99	96	97	98
RW 1 87.3 20 1 HR R S 2 R- R	RSW	99	99	96	97	98
RW 1 87.3 55 0 VW e - S 1 R- R	RSW	99	99	96	97	98
RW 1 87.4 40 0 VW n - S 1 R- L	RSW	98	99	97	97	98
RW 1 87.4 40 0 VW n - S 1 U- L	RSW	99	99	96	97	97
RW 1 87.6 15 0 VW m - S 1 R- R	RSW	99	99	97	97	98
RW 1 87.6 15 0 VW m - S 1 U- R	RSW	99	99	95	97	97
RW 1 87.6 45 0 VW f - S 1 R- L	RSW	99	99	96	97	98
RW 1 87.7 65 0 VW n - S 1 R- L	RSW	99	99	96	97	98
RW 1 89.2 0 0 VW a - S 1 R- R	RSW	99	99	97	97	98
RW 1 89.3 70 1 HR R S 1 R- R	RSW	99	97	97	97	98
RW 1 89.3 70 1 HR R S 2 R- R	RSW	99	96	97	97	98
RW 1 89.7 20 0 VW d - S 1 R- L	RSW	0	38			0
RW 1 89.8 95 1 HR L S 1 R- L	RSW	99	99	96	97	97
RW 1 89.8 95 1 HR L S 2 R- L	RSW	99	98	97	97	97
RW 1 89.9 5 1 HR R S 1 R- R	RSW	6	57	97	97	98
RW 1 89.9 5 1 HR R S 2 R- R	RSW	98	94	97	97	98
RW 1 90.8 95 1 HR L S 1 R- L	RSW	99	99	97	97	96
RW 1 90.8 95 1 HR L S 2 R- L	RSW	99	98	97	97	96
RW 1 93.4 20 0 VW m - S 1 R- R	RSW	99	99	97	97	98
RW 1 93.4 20 1 HR R S 1 R- R	RSW	99	99	97	97	98
RW 1 93.4 20 1 HR R S 2 R- R	RSW	99	98	97	97	98
RW 1 94.0 10 1 HR L S 1 R- L	RSW	99	99	97	97	98
RW 1 94.0 10 1 HR L S 2 R- L	RSW	99	99	97	97	98
RW 1 95.0 40 0 VW a - S 1 R- R	RSW	99	99	97	97	98
RW 1 95.0 65 1 HR L S 1 R- L	RSW	99	99	97	97	98
RW 1 95.0 65 1 HR L S 2 R- L	RSW	99	99	97	97	98
RW 1 95.0 75 1 HR R S 1 R- R	RSW	99	99	97	97	98
RW 1 95.0 75 1 HR R S 2 R- R	RSW	99	99	97	97	98
RW 1 96.1 55 1 HR R S 1 R- R	RSW	99	99	97	97	97
RW 1 96.1 55 1 HR R S 2 R- R	RSW	99	99	97	97	97

RW 1 96.4 40 1 HR L S 1 R- L	RSW	99	99	95	96	97
RW 1 96.4 40 1 HR L S 2 R- L	RSW	99	99	95	97	97
RW 1 98.7 23 1 HR L S 1 R- L	RSW	99	99	96	97	97
RW 1 98.7 23 1 HR L S 2 R- L	RSW	99	99	97	97	97
RW 1 98.7 23 1 HR L S 3 R- L	RSW	99	99	97	97	98
RW 28 27.3 0 0 VW x - S 1 R- R	RSW					
RW 28 27.3 0 0 VW x - S 2 R- R	RSW					
RW 28 27.3 35 0 VW r - S 1 R- R	RSW	87	98	98	97	98
RW 28 27.3 35 0 VW r - S 2 R- R	RSW					
RW 28 27.3 60 0 VW w - S 1 R- L	RSW	94	94	92	85	96
RW 28 27.3 60 0 VW y - S 1 R- L	RSW	99	90	65	79	96
RW 28 27.3 60 0 VW y - S 2 R- L	RSW	94	92	69	75	96
RW 28 27.4 15 1 HR R S 1 R- R	RSW	68	17	99	97	98
RW 28 27.4 15 1 HR R S 2 R- R	RSW	68	17	99	97	98
RW 28 27.5 80 0 VW s - S 1 R- L	RSW	98	98	99	97	98
RW 28 27.5 80 0 VW s - S 2 R- L	RSW					0
RW 28 27.6 50 0 VW v - S 1 R- R	RSW	88	94	98	96	91
RW 28 27.6 50 0 VW x - S 1 R- R	RSW	88	23	99	97	97
RW 28 27.6 50 0 VW x - S 2 R- R	RSW	88	23	99	97	97
RW 28 27.6 70 0 VW y - S 1 R- L	RSW	99	96	92	85	97
RW 28 27.6 70 0 VW y - S 2 R- L	RSW	94	94	92	85	96
RW 28 27.6 70 1 HR L S 1 R- L	RSW	99	96	93	85	97
RW 28 27.6 70 1 HR L S 2 R- L	RSW	99	95	93	85	96
RW 28 28.6 0 1 HR R S 1 R- R	RSW	99	96	94	81	89
RW 28 28.6 0 1 HR R S 2 R- R	RSW	99	96	94	81	89
RW 28 31.4 35 1 HR L S 1 R- L	RSW	99	99	85	0	
RW 28 31.4 35 1 HR L S 2 R- L	RSW	99	99	85	0	
RW 28 31.4 45 1 HR R S 1 R- R	RSW	99	99	85		
RW 28 31.4 45 1 HR R S 2 R- R	RSW	99	99	85		
RW 28 35.3 5 1 HR L S 1 R- L	RSW	99	91	88	76	85
RW 28 35.3 5 1 HR L S 2 R- L	RSW	99	91	88	76	85
RW 28 35.3 5 1 HR R S 1 R- R	RSW	99	97	94	86	96
RW 28 35.3 5 1 HR R S 2 R- R	RSW	99	97	94	86	97
RW 28 36.2 50 1 HR R S 1 R- R	RSW	99	99	84		0
RW 28 36.2 50 1 HR R S 2 R- R	RSW	99	99	84		0
RW 28 36.2 60 1 HR L S 1 R- L	RSW	99	98	84		0
RW 28 36.2 60 1 HR L S 2 R- L	RSW	92	90	82		0
RW 28 36.8 50 1 HR R S 1 R- R	RSW	99	99	84		0
RW 28 36.8 50 1 HR R S 2 R- R	RSW	97	98	84		0
RW 28 36.9 0 1 HR L S 1 R- L	RSW	99	98	84		0
RW 28 36.9 0 1 HR L S 2 R- L	RSW	99	97	84		0
RW 50 202.1 30 1 HR L S 1 R- L	RSW	99	99	97	97	97
RW 50 202.1 30 1 HR L S 2 R- L	RSW	99	99	96	97	97
RW 50 202.1 30 1 HR R S 1 R- R	RSW					
RW 50 202.1 30 1 HR R S 2 R- R	RSW					
RW 50 202.1 75 1 HR R S 1 U- R	RSW	99	99	97	97	98
RW 50 202.1 80 1 HR L S 1 I- L	RSW	99	99	97	97	97
RW 50 203.8 35 0 VW x - S 1 R- R	RSW	98	99	96	97	97
RW 50 203.8 35 1 HR R S 1 R- R	RSW	99	99	97	97	97
RW 50 203.8 35 1 HR R S 2 R- R	RSW	99	99	96	97	97
RW 50 203.8 80 0 VW y - S 1 R- L	RSW	99	99	96	97	98
RW 50 203.8 80 0 VW y - S 1 U- L	RSW	99	99	97	97	98
RW 50 203.9 5 0 VW r - S 1 R- R	RSW	99	99	97	97	98
RW 50 204.0 95 0 VW s - S 1 R- L	RSW	98	99	97	97	98
RW 50 204.1 25 0 VW x - S 1 R- R	RSW	99	99	96	97	98

RW 50 204.1 25 0 VW x - S 1 U- R	RSW	98	99	97	97	98
RW 50 204.1 70 0 VW y - S 1 R- L	RSW	99	99	96	97	97
RW 50 204.1 70 1 HR L S 1 R- L	RSW	99	99	97	97	97
RW 50 204.1 70 1 HR L S 2 R- L	RSW	99	99	96	97	97
RW 50 205.9 30 0 VW d - S 1 R- L	RSW	99	99	97	97	98
RW 50 205.9 30 1 HR L S 1 R- L	RSW	99	99	97	97	98
RW 50 205.9 30 1 HR L S 2 R- L	RSW	99	99	96	97	98
RW 50 206.0 15 0 VW m - S 1 R- R	RSW	99	99	97	97	98
RW 50 206.0 50 0 VW b - S 1 R- R	RSW	99	99	97	97	98
RW 50 206.2 15 1 HR R S 1 R- R	RSW	99	98	96	97	97
RW 50 206.2 15 1 HR R S 2 R- R	RSW	99	99	97	97	98
RW 50 206.4 40 0 VW a - S 1 R- R	RSW	0	0	8	97	98
RW 50 206.5 0 0 VW m - S 1 R- R	RSW	99	99	97	97	98
RW 50 207.3 0 1 HR L S 1 R- L	RSW	99	99	97	97	98
RW 50 207.3 0 1 HR L S 2 R- L	RSW	99	99	96	97	98
RW 50 207.3 0 1 HR R S 1 R- R	RSW	99	98	96	97	97
RW 50 207.3 0 1 HR R S 2 R- R	RSW	99	99	97	97	98
Observation point (BPS-attributes)	Type	apr '01	may '01	jun '01	jul '01	aug '01

APPENDIX

E

Detector location

srt_ na	weg_ num	km_ pnt	afs	srt_ na	pos_ ba	rel_ vg	dvk_ le	srt_ na	pos_ rs	rel_ vg	bps_ cod	rank
RW	1	834	70	HR	L	1		R-	L	1	00D0010D0846D0050005	1
RW	1	834	70	HR	L	1		R-	L	2	00D0010D0846D0050009	2
RW	1	840	95	HR	L	1		R-	L	1	00D0010D205FD0050005	3
RW	1	840	95	HR	L	1		R-	L	2	00D0010D205FD0050009	4
RW	1	841	5	HR	R	1		R-	R	1	00D0010D2405D0070007	5
RW	1	841	5	HR	R	1		R-	R	2	00D0010D2405D007000B	6
RW	1	846	15	HR	R	1		R-	R	1	00D0010D380FD0070007	7
RW	1	846	15	HR	R	1		R-	R	2	00D0010D380FD007000B	8
RW	1	851	15	HR	L	1		R-	L	1	00D0010D4C0FD0050005	9
RW	1	851	15	HR	L	1		R-	L	2	00D0010D4C0FD0050009	10
RW	1	873	10	HR	L	1		R-	L	1	00D0010DA40AD0050005	11
RW	1	873	10	HR	L	1		R-	L	2	00D0010DA40AD0050009	12
RW	1	873	20	HR	R	1		R-	R	1	00D0010DA414D0070007	13
RW	1	873	20	HR	R	1		R-	R	2	00D0010DA414D007000B	14
RW	1	873	55	VW	N	0	e	R-	R	1	00D0010DA43720200007	15
RW	1	874	40	VW	N	0	n	R-	L	1	00D0010DA82868200005	16
RW	1	874	40	VW	N	0	n	U-	L	1	00D0010DA82868200085	17
RW	1	876	15	VW	N	0	m	R-	R	1	00D0010DB00F60200007	18
RW	1	876	15	VW	N	0	m	U-	R	1	00D0010DB00F60200087	19
RW	1	876	45	VW	N	0	f	R-	L	1	00D0010DB02D28200005	20
RW	1	877	65	VW	N	0	n	R-	L	1	00D0010DB44168200005	21
RW	1	892	0	VW	N	0	a	R-	R	1	00D0010DF00000200007	22
RW	1	893	70	HR	R	1		R-	R	1	00D0010DF446D0070007	23
RW	1	893	70	HR	R	1		R-	R	2	00D0010DF446D007000B	24
RW	1	898	95	HR	L	1		R-	L	1	00D0010E085FD0050005	25
RW	1	898	95	HR	L	1		R-	L	2	00D0010E085FD0050009	26
RW	1	899	5	HR	R	1		R-	R	2	00D0010E0C05D007000B	27
RW	1	908	95	HR	L	1		R-	L	1	00D0010E305FD0050005	28
RW	1	908	95	HR	L	1		R-	L	2	00D0010E305FD0050009	29
RW	1	934	20	VW	N	0	m	R-	R	1	00D0010E981460200007	30
RW	1	934	20	HR	R	1		R-	R	1	00D0010E9814D0070007	31
RW	1	934	20	HR	R	1		R-	R	2	00D0010E9814D007000B	32
RW	1	940	10	HR	L	1		R-	L	1	00D0010EB00AD0050005	33
RW	1	940	10	HR	L	1		R-	L	2	00D0010EB00AD0050009	34
RW	1	950	40	VW	N	0	a	R-	R	1	00D0010ED82800200007	35
RW	1	950	65	HR	L	1		R-	L	1	00D0010ED841D0050005	36
RW	1	950	65	HR	L	1		R-	L	2	00D0010ED841D0050009	37
RW	1	950	75	HR	R	1		R-	R	1	00D0010ED84BD0070007	38
RW	1	950	75	HR	R	1		R-	R	2	00D0010ED84BD007000B	39
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RW	1	964	40	HR	L	1		R-	L	1	00D0010F1028D0050005	42
RW	1	964	40	HR	L	1		R-	L	2	00D0010F1028D0050009	43
RW	1	987	23	HR	L	1		R-	L	1	00D0010F6C17D0050005	44

RW	1	987	23	HR	L	1		R-	L	2	00D0010F6C17D0050009	45
RW	1	987	23	HR	L	1		R-	L	3	00D0010F6C17D005000D	46
RW	1	1042	85	HR	R	1		R-	R	1	00D001104855D0070007	47
RW	1	1042	85	HR	R	1		R-	R	2	00D001104855D007000B	48
RW	1	1042	95	VW	N	0	d	R-	L	1	00D00110485F18200005	49
RW	1	1049	90	VW	N	0	a	R-	R	1	00D00110645A00200007	50
RW	1	1050	70	HR	L	1		R-	L	1	00D001106846D0050005	51
RW	1	1050	70	HR	L	1		R-	L	2	00D001106846D0050009	52
RW	1	1050	80	HR	R	1		R-	R	1	00D001106850D0070007	53
RW	1	1050	80	HR	R	1		R-	R	2	00D001106850D007000B	54
RW	1	1050	95	VW	N	0	c	R-	L	1	00D00110685F10200005	55
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RW	1	1060	45	HR	L	1		R-	L	1	00D00110902DD0050005	57
RW	1	1060	45	HR	L	1		R-	L	2	00D00110902DD0050009	58
RW	1	1060	55	HR	R	1		R-	R	1	00D001109037D0070007	59
RW	1	1060	55	HR	R	1		R-	R	2	00D001109037D007000B	60
RW	1	1070	75	HR	L	1		R-	L	1	00D00110B84BD0050005	61
RW	1	1070	75	HR	L	1		R-	L	2	00D00110B84BD0050009	62
RW	1	1070	85	HR	R	1		R-	R	1	00D00110B855D0070007	63
RW	1	1070	85	HR	R	1		R-	R	2	00D00110B855D007000B	64
RW	1	1076	75	HR	R	1		R-	R	1	00D00110D04BD0070007	65
RW	1	1076	75	HR	R	1		R-	R	2	00D00110D04BD007000B	66
RW	1	1080	85	HR	L	1		R-	L	1	00D00110E055D0050005	67
RW	1	1080	85	HR	L	1		R-	L	2	00D00110E055D0050009	68
RW	50	2021	30	HR	L	1		R-	L	1	00D0321F941ED0050005	69
RW	50	2021	30	HR	L	1		R-	L	2	00D0321F941ED0050009	70
RW	50	2021	75	HR	R	1		U-	R	1	00D0321F944BD0070087	71
RW	50	2021	80	HR	L	1		I-	L	1	00D0321F9450D0050105	72
RW	50	2038	35	VW	N	0	x	R-	R	1	00D0321FD823B8200007	73
RW	50	2038	35	HR	R	1		R-	R	1	00D0321FD823D0070007	74
RW	50	2038	35	HR	R	1		R-	R	2	00D0321FD823D007000B	75
RW	50	2038	80	VW	N	0	y	R-	L	1	00D0321FD850C0200005	76
RW	50	2038	80	VW	N	0	y	U-	L	1	00D0321FD850C0200085	77
RW	50	2039	5	VW	N	0	r	R-	R	1	00D0321FDC0588200007	78
RW	50	2040	95	VW	N	0	s	R-	L	1	00D0321FE05F90200005	79
RW	50	2041	25	VW	N	0	x	R-	R	1	00D0321FE419B8200007	80
RW	50	2041	25	VW	N	0	x	U-	R	1	00D0321FE419B8200087	81
RW	50	2041	70	VW	N	0	y	R-	L	1	00D0321FE446C0200005	82
RW	50	2041	70	HR	L	1		R-	L	1	00D0321FE446D0050005	83
RW	50	2041	70	HR	L	1		R-	L	2	00D0321FE446D0050009	84
RW	50	2059	30	VW	N	0	d	R-	L	1	00D032202C1E18200005	85
RW	50	2059	30	HR	L	1		R-	L	1	00D032202C1ED0050005	86
RW	50	2059	30	HR	L	1		R-	L	2	00D032202C1ED0050009	87
RW	50	2060	15	VW	N	0	m	R-	R	1	00D03220300F60200007	88
RW	50	2060	50	VW	N	0	b	R-	R	1	00D0322030320820007	89
RW	50	2062	15	HR	R	1		R-	R	1	00D03220380FD0070007	90
RW	50	2062	15	HR	R	1		R-	R	2	00D03220380FD007000B	91

RW	50	2065	0	VW	N	0	m	R-	R	1	00D03220440060200007	92
RW	50	2073	0	HR	L	1		R-	L	1	00D032206400D0050005	93
RW	50	2073	0	HR	L	1		R-	L	2	00D032206400D0050009	94
RW	50	2073	0	HR	R	1		R-	R	1	00D032206400D0070007	95
RW	50	2073	0	HR	R	1		R-	R	2	00D032206400D007000B	96
RW	1	442	50	VW	N	0	e	R-	R	1	00D00106E83220200007	1
RW	1	442	50	VW	N	0	e	R-	R	2	00D00106E8322020000B	2
RW	1	442	50	VW	N	0	m	R-	R	1	00D00106E83260200007	3
RW	1	442	50	VW	N	0	m	R-	R	2	00D00106E8326020000B	4
RW	1	443	50	VW	N	0	n	R-	L	1	00D00106EC3268200005	5
RW	1	443	50	VW	N	0	n	R-	L	2	00D00106EC3268200009	6
RW	1	444	0	VW	N	0	k	R-	L	1	00D00106F00050200005	7
RW	1	445	85	HR	R	1		R-	R	1	00D00106F455D0070007	8
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RW	1	446	35	HR	L	1		R-	L	1	00D00106F823D0050005	10
RW	1	446	35	HR	L	1		R-	L	2	00D00106F823D0050009	11
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RW	1	448	50	VW	N	0	m	R-	R	2	00D0010700326020000B	13
RW	1	449	0	VW	N	0	f	R-	L	1	00D00107040028200005	14
RW	1	449	0	VW	N	0	f	R-	L	2	00D00107040028200009	15
RW	1	454	15	VW	N	0	a	R-	R	1	00D00107180F00200007	16
RW	1	454	50	VW	N	0	m	R-	R	1	00D00107183260200007	17
RW	1	454	50	VW	N	0	m	R-	R	2	00D0010718326020000B	18
RW	1	454	85	VW	N	0	n	R-	L	1	00D00107185568200005	19
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RW	1	464	35	HR	R	1		R-	R	1	00D001074023D0070007	21
RW	1	464	35	HR	R	1		R-	R	2	00D001074023D007000B	22
RW	1	469	45	HR	L	1		R-	L	1	00D00107542DD0050005	23
RW	1	469	45	HR	L	1		R-	L	2	00D00107542DD0050009	24
RW	1	492	85	HR	L	1		R-	L	1	00D00107B055D0050005	25
RW	1	492	85	HR	L	1		R-	L	2	00D00107B055D0050009	26
RW	1	492	95	HR	R	1		R-	R	1	00D00107B05FD0070007	27
RW	1	492	95	HR	R	1		R-	R	2	00D00107B05FD007000B	28
RW	28	273	35	VW	N	0	r	R-	R	1	00D01C04442388200007	29
RW	28	273	60	VW	N	0	w	R-	L	1	00D01C04443CB0200005	30
RW	28	273	60	VW	N	0	y	R-	L	1	00D01C04443CC0200005	31
RW	28	273	60	VW	N	0	y	R-	L	2	00D01C04443CC0200009	32
RW	28	275	80	VW	N	0	s	R-	L	1	00D01C044C5090200005	33
RW	28	276	50	VW	N	0	v	R-	R	1	00D01C045032A8200007	34
RW	28	276	70	VW	N	0	y	R-	L	1	00D01C045046C0200005	35
RW	28	276	70	VW	N	0	y	R-	L	2	00D01C045046C0200009	36
RW	28	276	70	HR	L	1		R-	L	1	00D01C045046D0050005	37
RW	28	276	70	HR	L	1		R-	L	2	00D01C045046D0050009	38
RW	28	286	0	HR	R	1		R-	R	1	00D01C047800D0070007	39
RW	28	286	0	HR	R	1		R-	R	2	00D01C047800D007000B	40

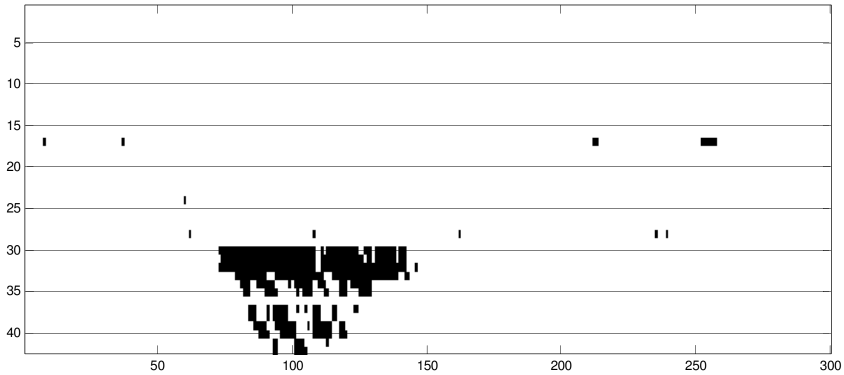
RW	28	314	35	HR	L	1		R-	L	1	00D01C04E823D0050005	41
RW	28	314	35	HR	L	1		R-	L	2	00D01C04E823D0050009	42
RW	28	314	45	HR	R	1		R-	R	1	00D01C04E82DD0070007	43
RW	28	314	45	HR	R	1		R-	R	2	00D01C04E82DD007000B	44
RW	28	353	5	HR	L	1		R-	L	1	00D01C058405D0050005	45
RW	28	353	5	HR	L	1		R-	L	2	00D01C058405D0050009	46
RW	28	353	5	HR	R	1		R-	R	1	00D01C058405D0070007	47
RW	28	353	5	HR	R	1		R-	R	2	00D01C058405D007000B	48
RW	28	362	50	HR	R	1		R-	R	1	00D01C05A832D0070007	49
RW	28	362	50	HR	R	1		R-	R	2	00D01C05A832D007000B	50
RW	28	362	60	HR	L	1		R-	L	1	00D01C05A83CD0050005	51
RW	28	362	60	HR	L	1		R-	L	2	00D01C05A83CD0050009	52
RW	28	368	50	HR	R	1		R-	R	1	00D01C05C032D0070007	53
RW	28	368	50	HR	R	1		R-	R	2	00D01C05C032D007000B	54
RW	28	369	0	HR	L	1		R-	L	1	00D01C05C400D0050005	55
RW	28	369	0	HR	L	1		R-	L	2	00D01C05C400D0050009	56
srt_na	weg_num	km_pnt	afs	srt_na	pos_ba	rel_vg	dvk_le	srt_na	pos_rs	rel_vg	bps_cod	rank

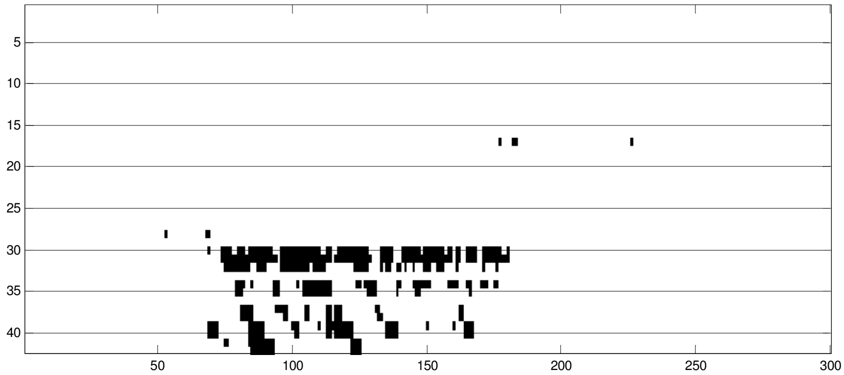
APPENDIX

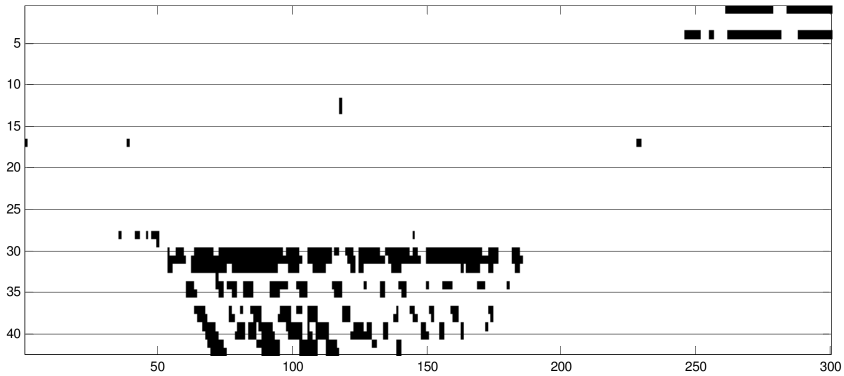
F

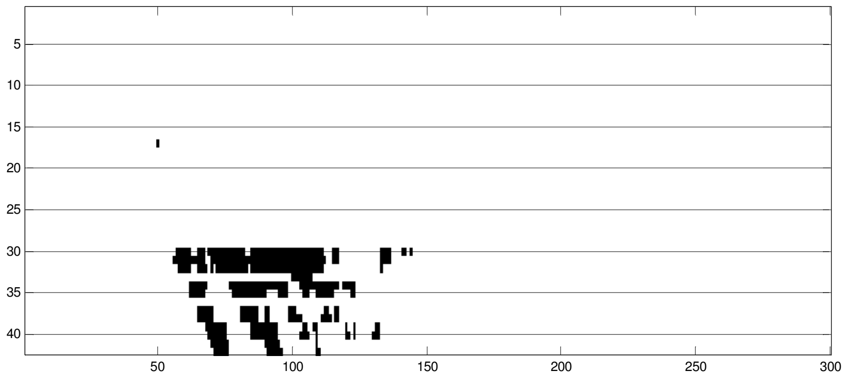
Congestion graphs – Beekbergen morning peak

Beekbergen a.m. peak – Mondays (7th, 14th, 21st, 28th of May 2001).

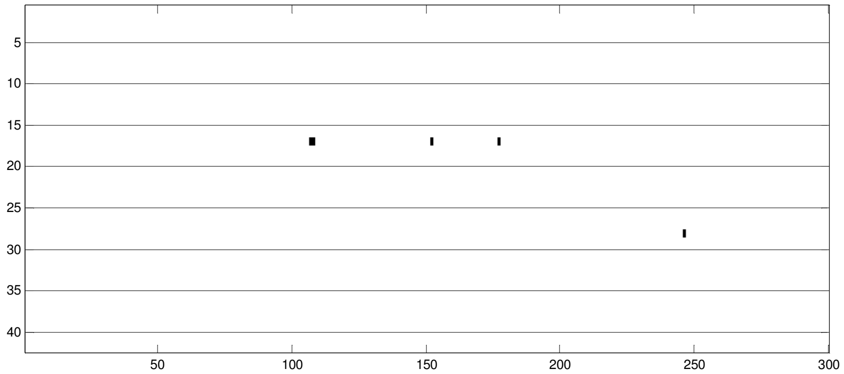


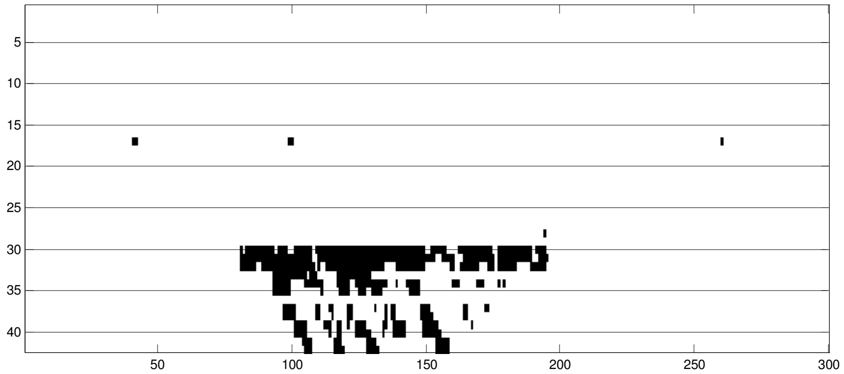


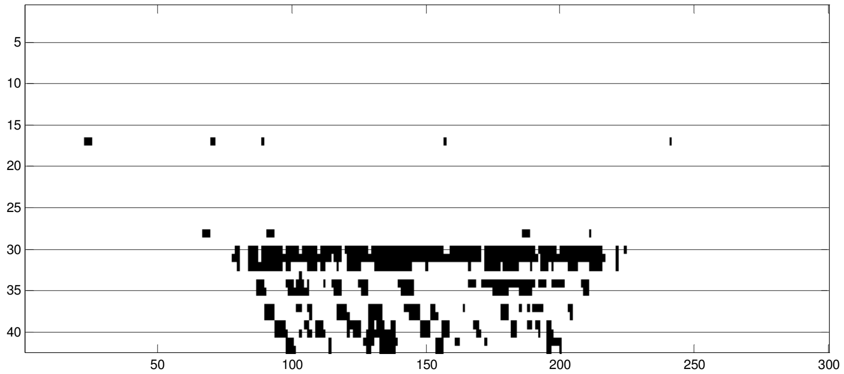


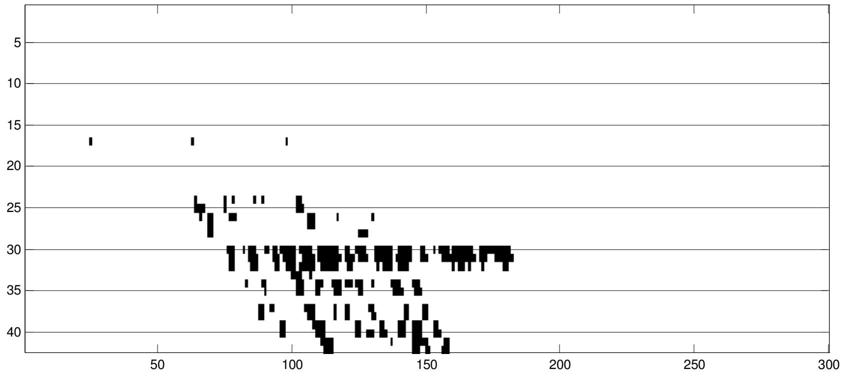


Beekbergen a.m. peak – Tuesdays (1st, 8th, 15th, 22nd of May 2001).

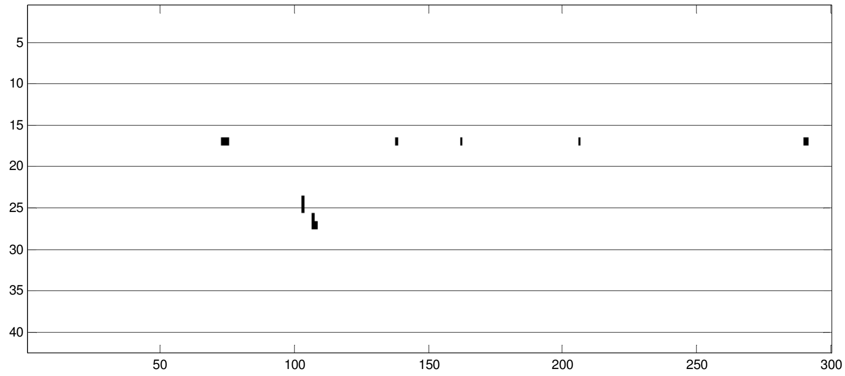


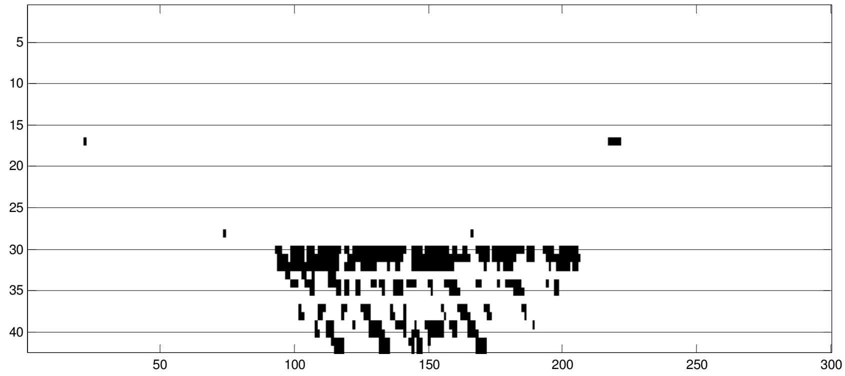


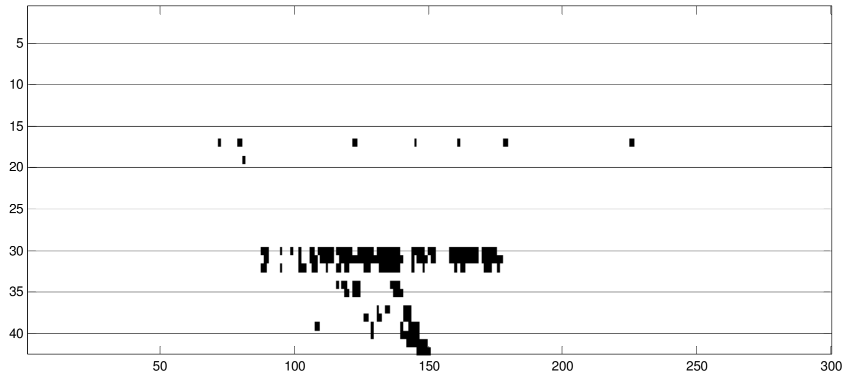


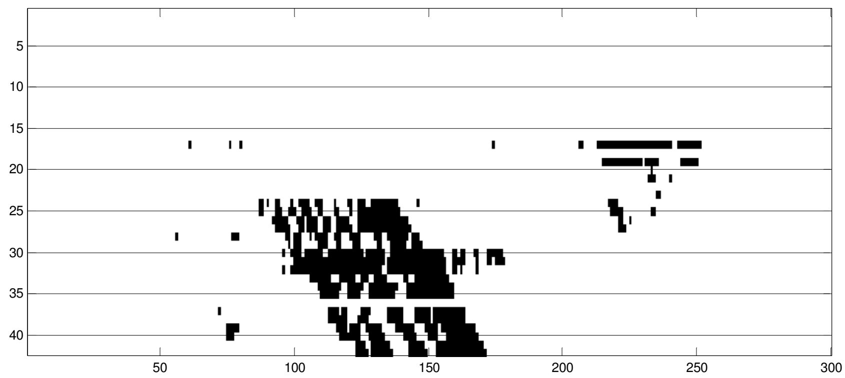


Beekbergen a.m. peak – Wednesdays (2nd, 9th, 16th, 30th of May 2001).

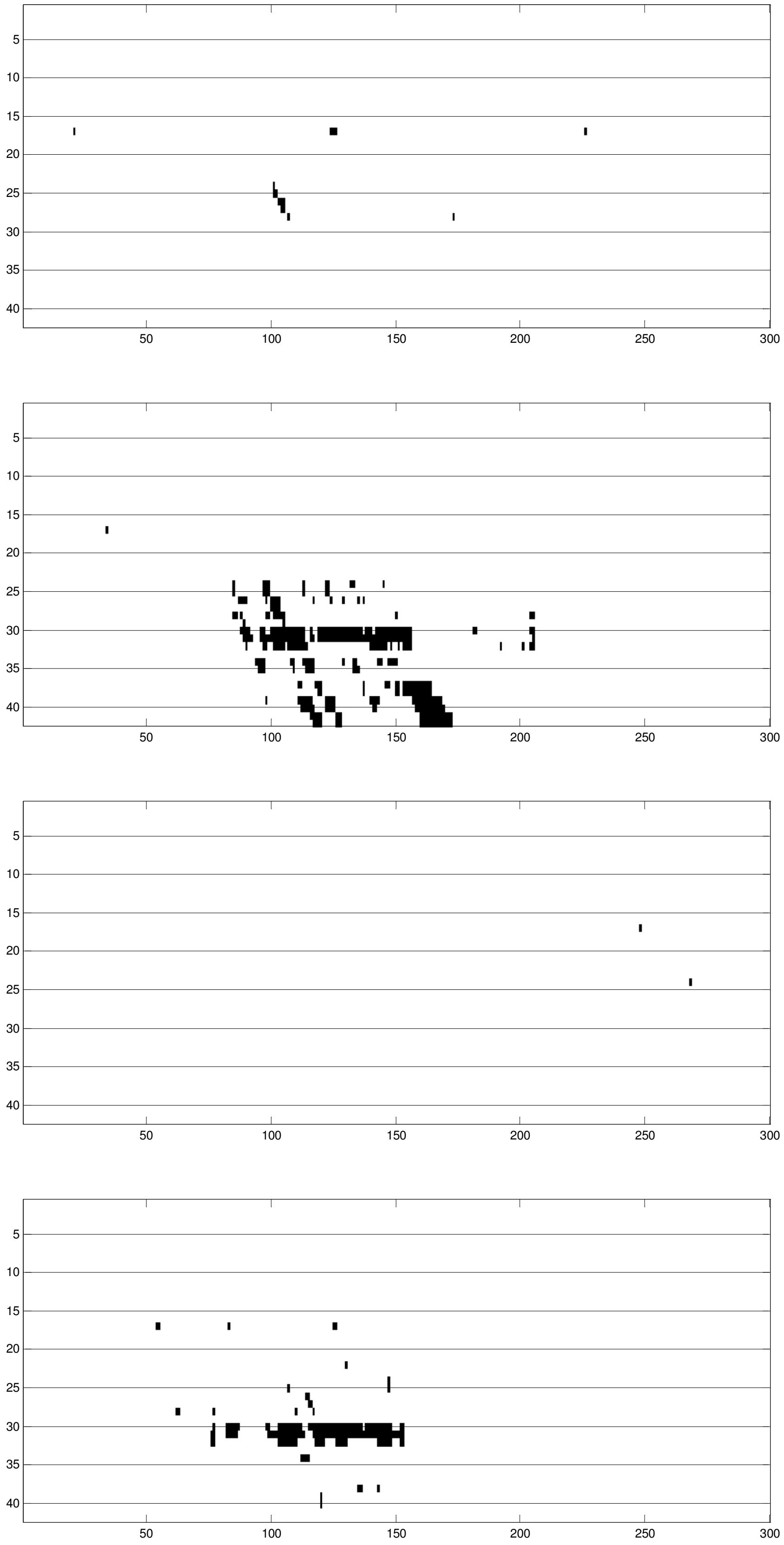




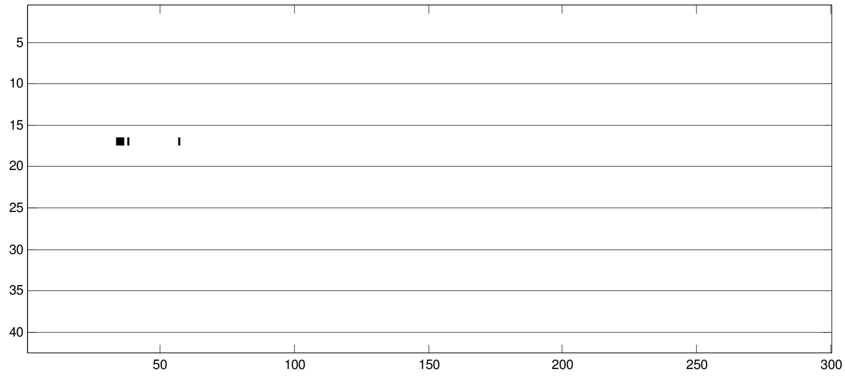


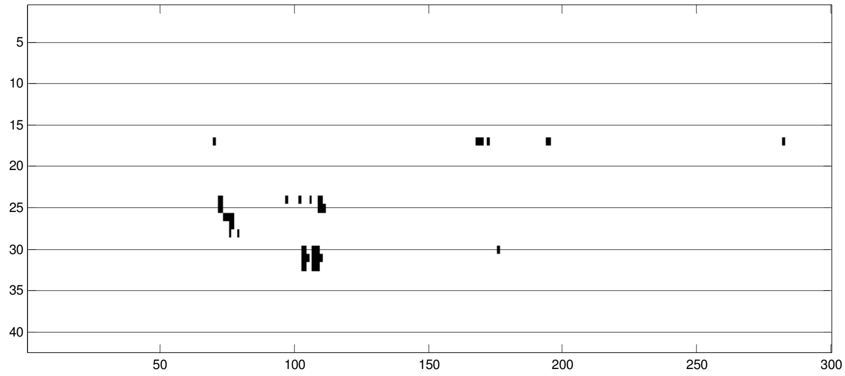


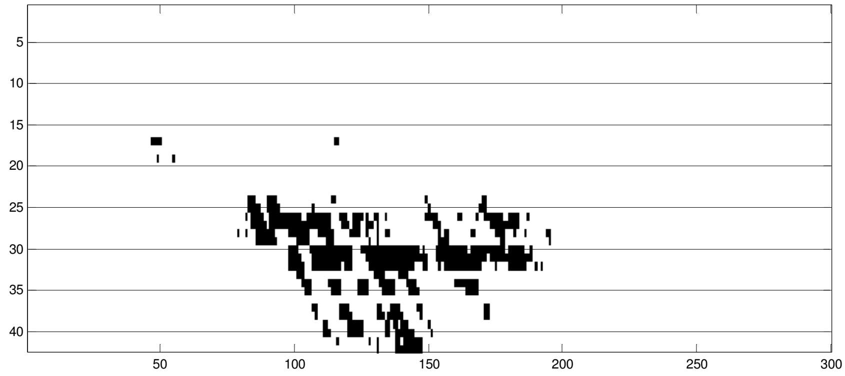
Beekbergen a.m. peak – Thursdays (3rd, 17th, 24th, 31st of May 2001).

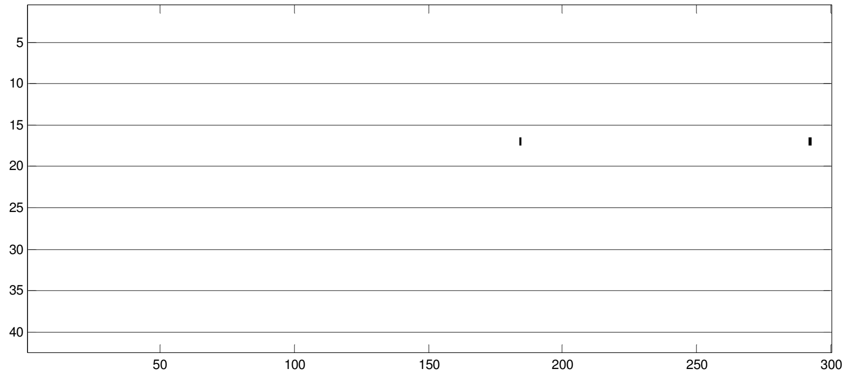


Beekbergen a.m. peak – Fridays (4th, 11th, 18th, 25th of May 2001).







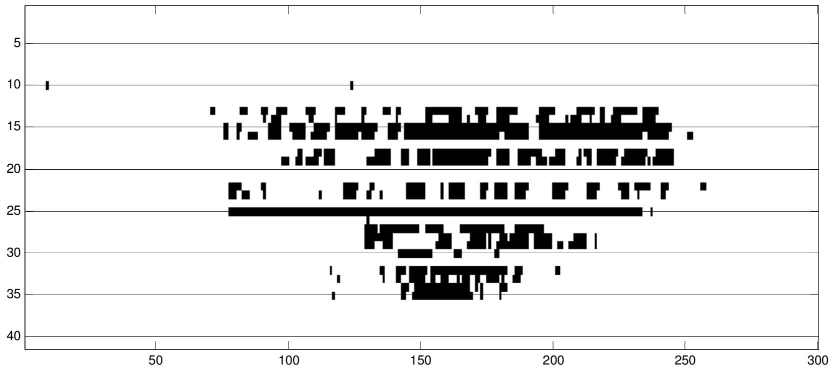


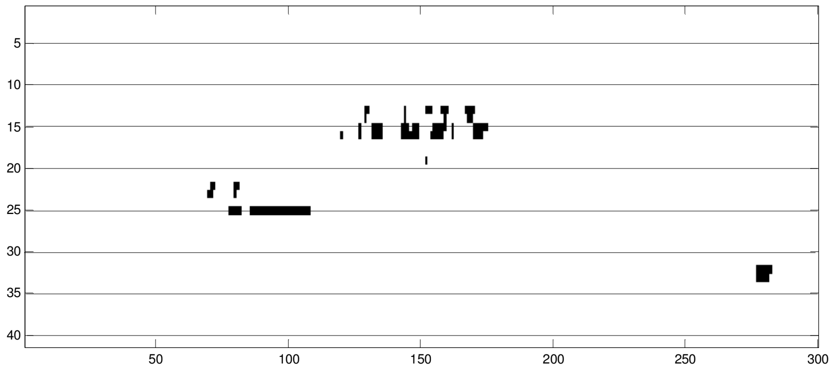
APPENDIX

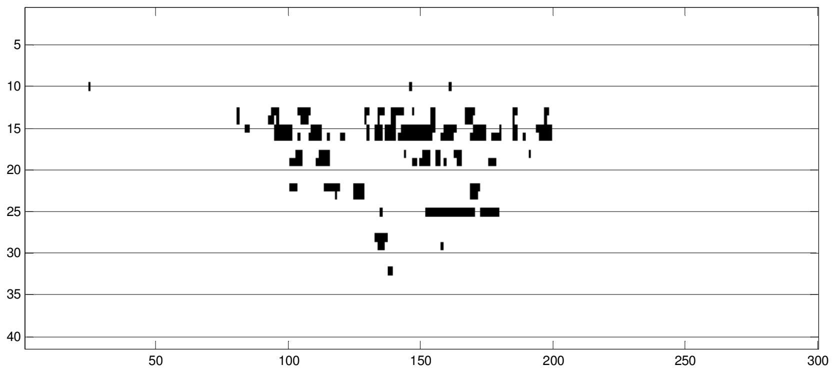
G

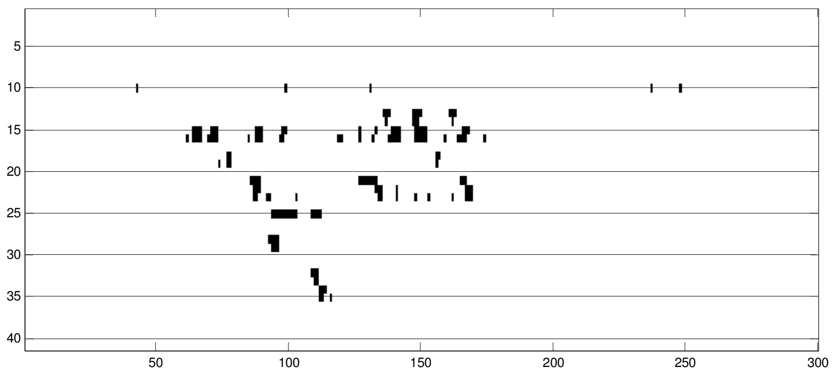
Congestion graphs – Beekbergen evening peak

Beekbergen p.m. peak – Mondays (7th, 14th, 21st, 28th of May 2001).

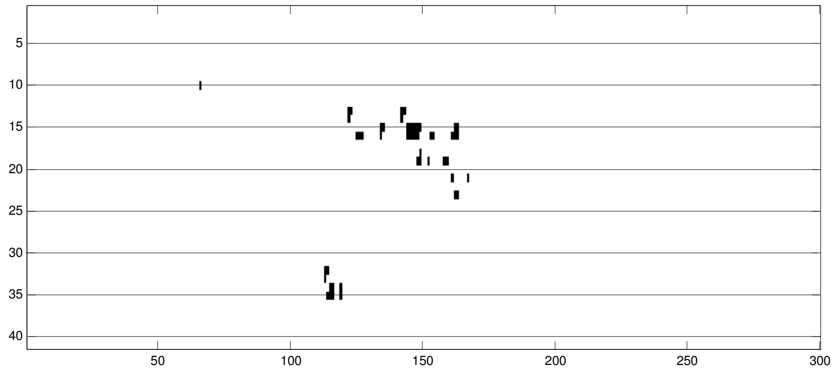


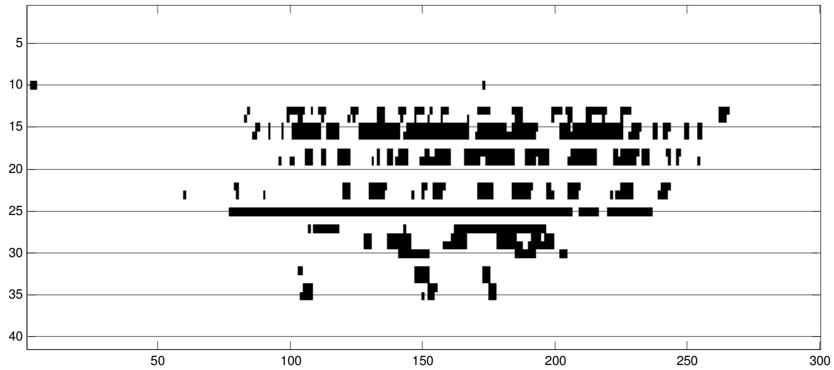


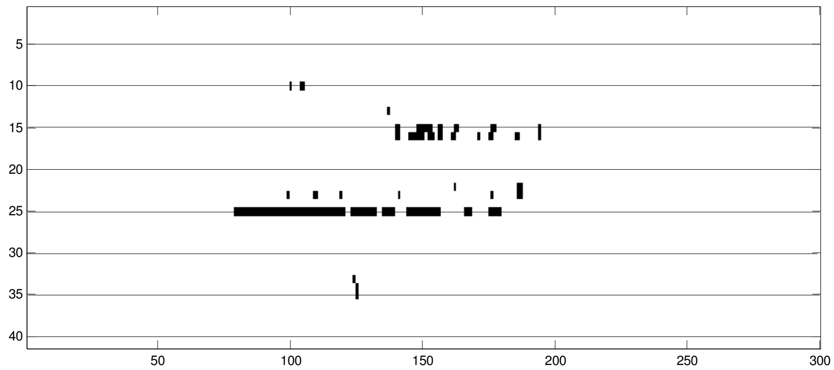


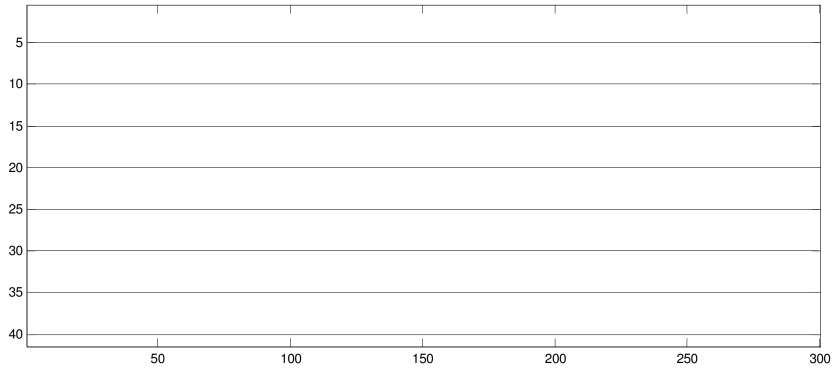


Beekbergen p.m. peak – Tuesdays (1st, 8th, 15th, 22nd of May 2001).

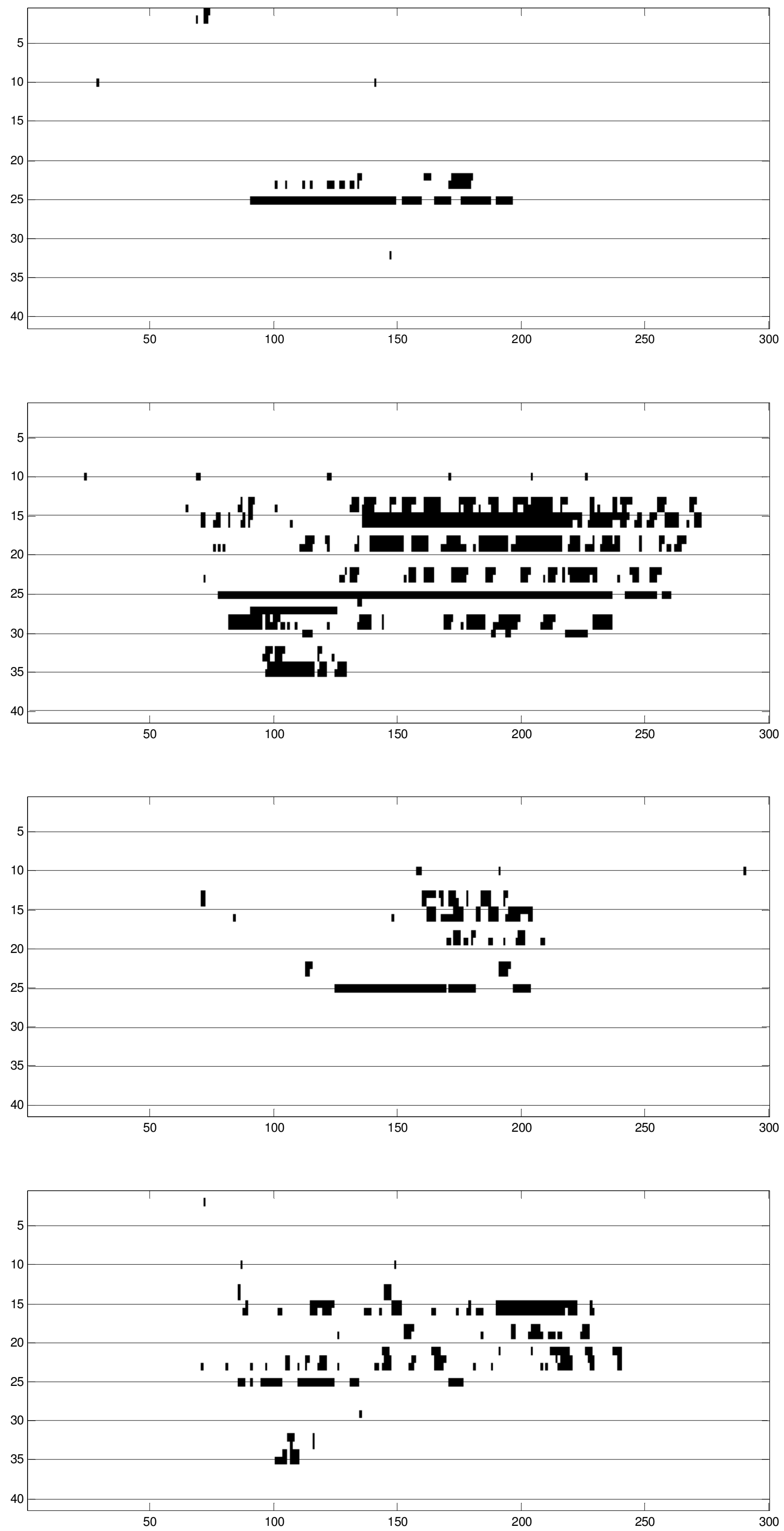




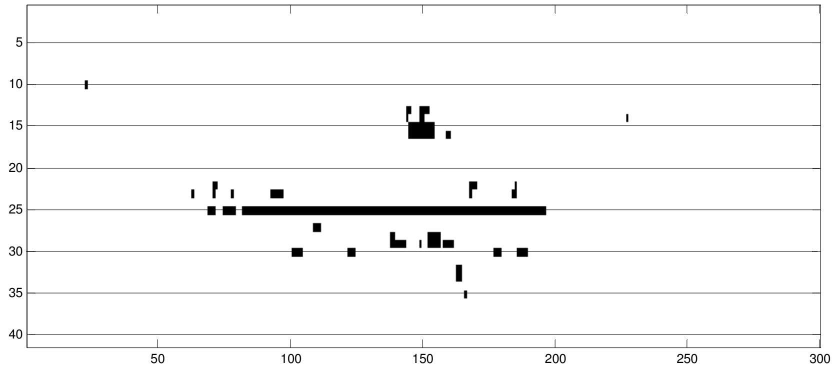


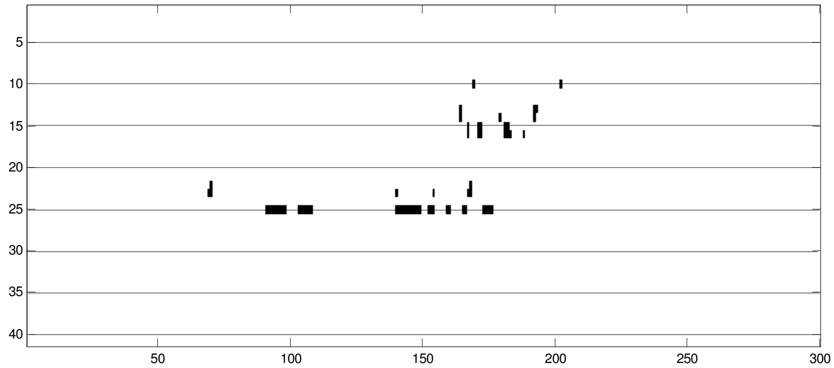


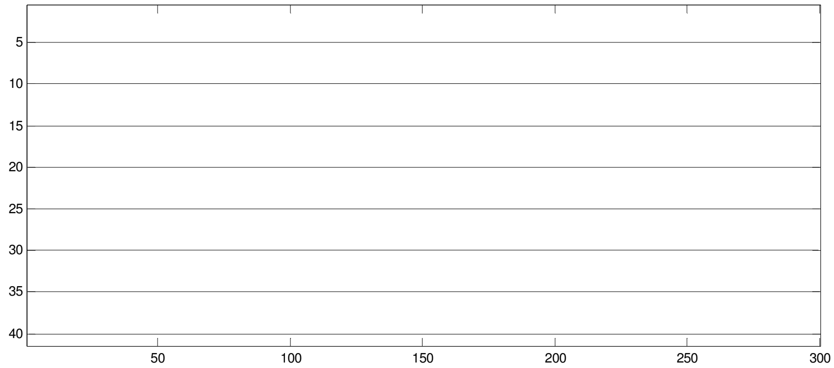
Beekbergen p.m. peak – Wednesdays (2nd, 9th, 16th, 30th of May 2001).

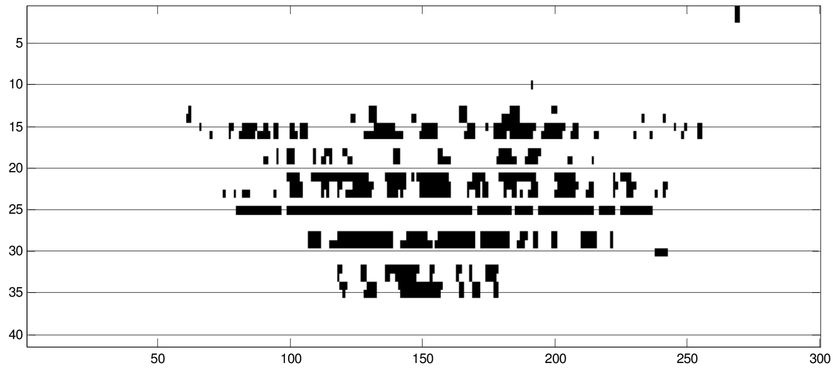


Beekbergen p.m. peak – Thursdays (3rd, 17th, 24th, 31st of May 2001).

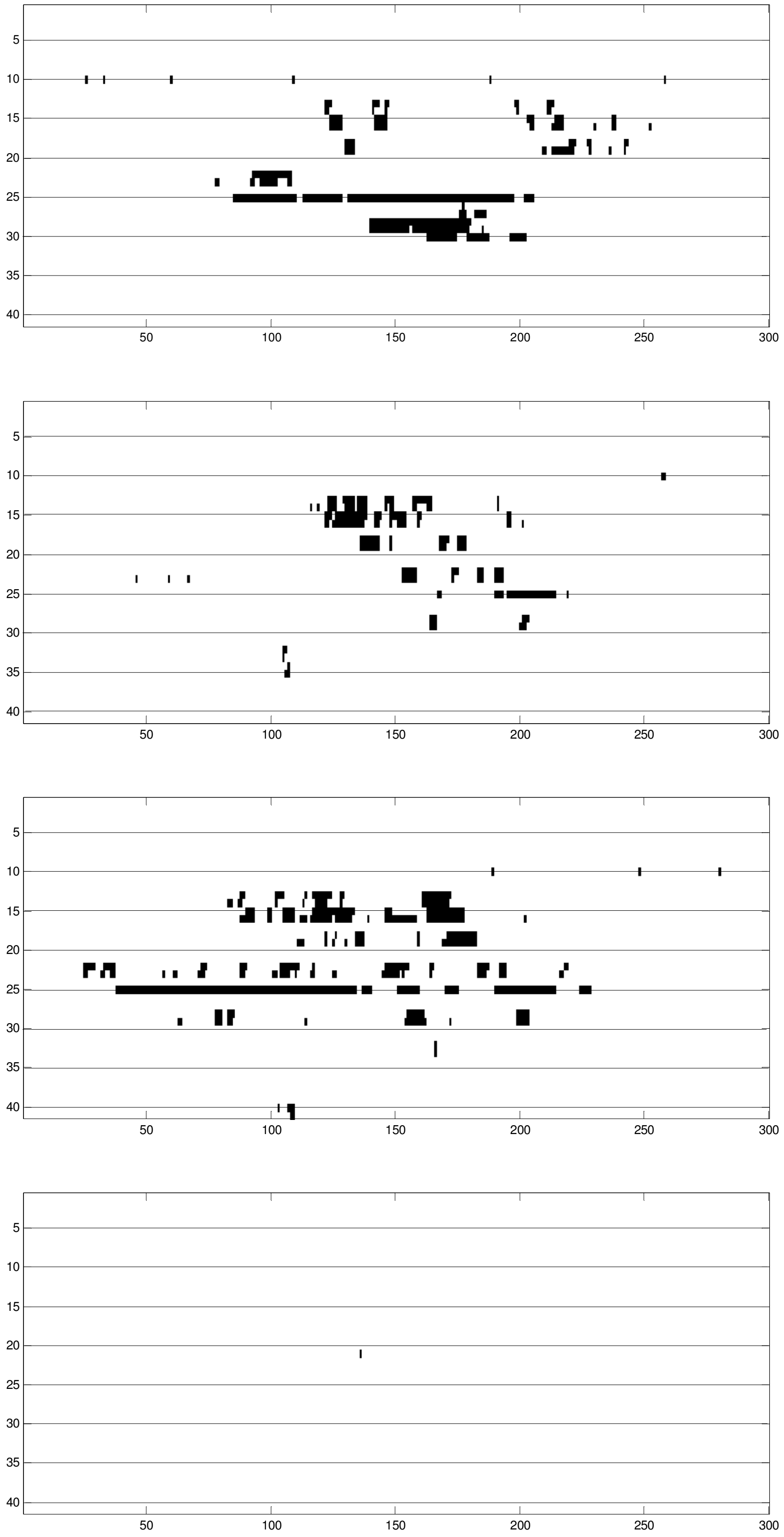








Beekbergen p.m. peak – Fridays (4th, 11th, 18th, 25th of May 2001).

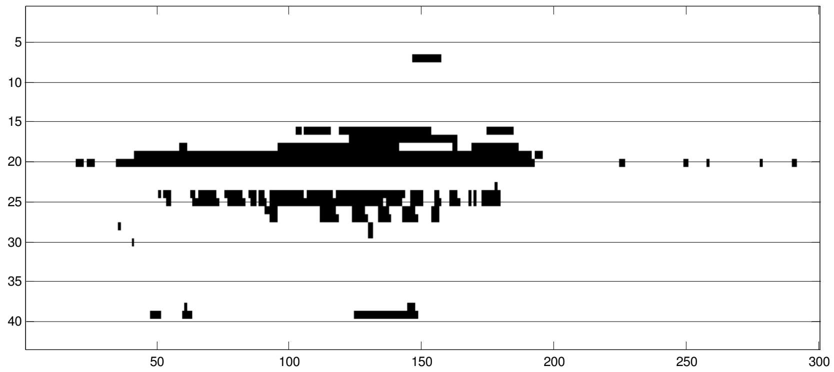


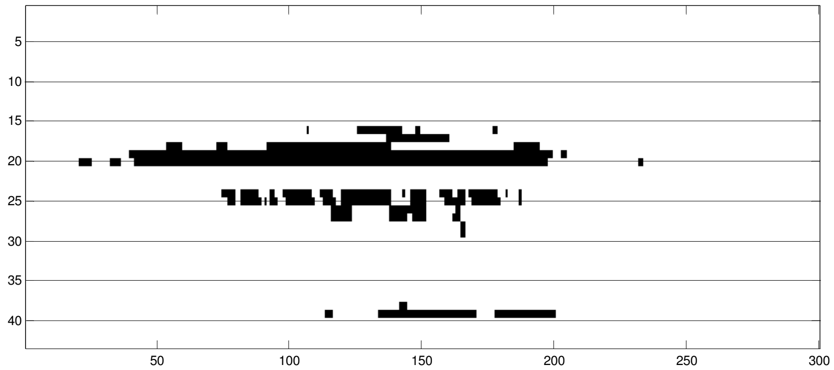
APPENDIX

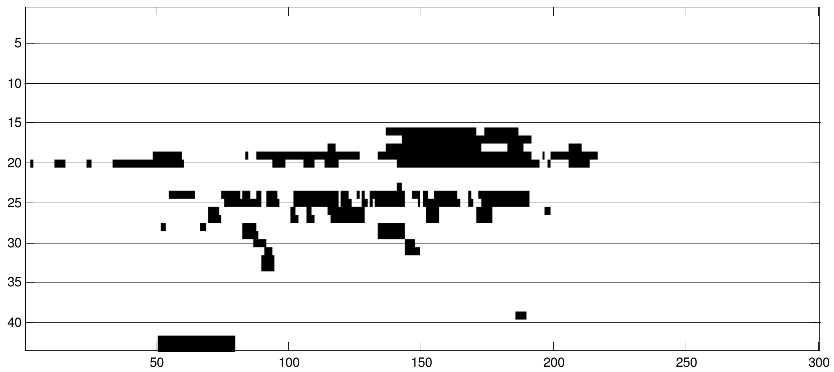
H

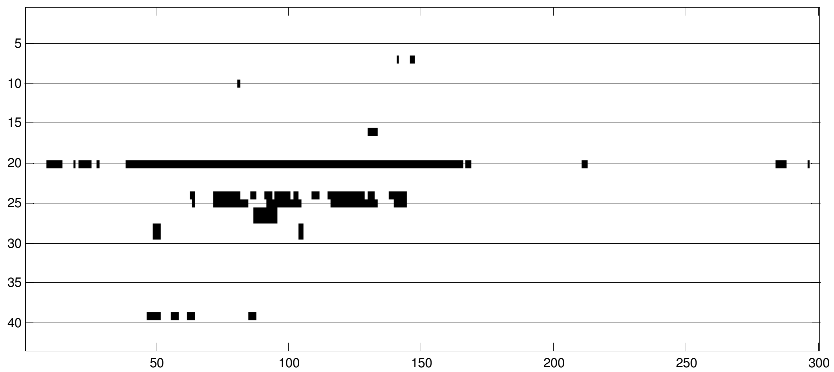
Congestion graphs – Hoevelaken morning peak

Hoevelaken a.m. peak – Mondays (7th, 14th, 21st, 28th of May 2001).

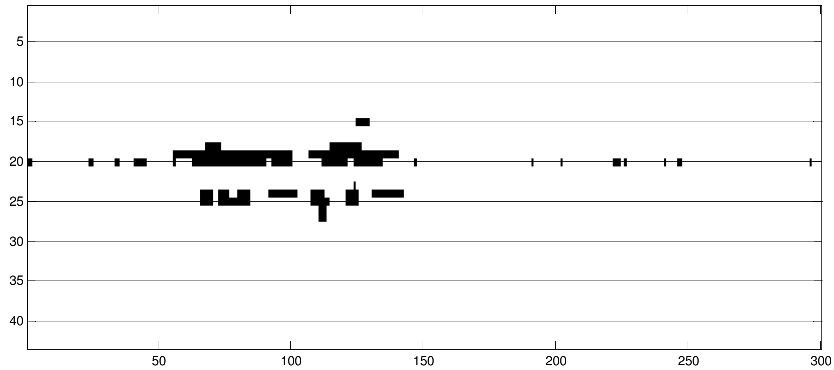


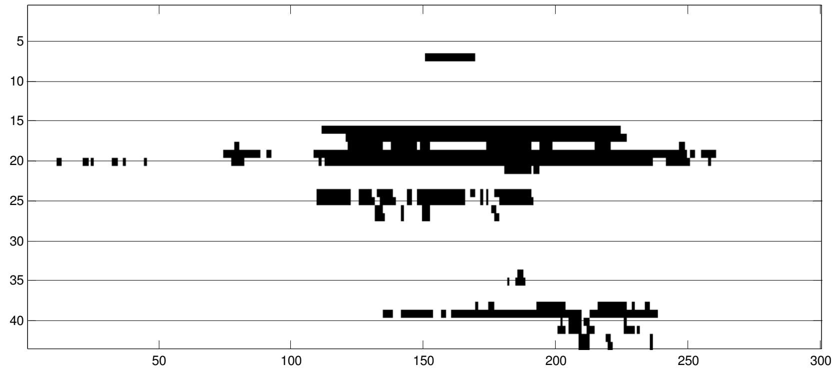


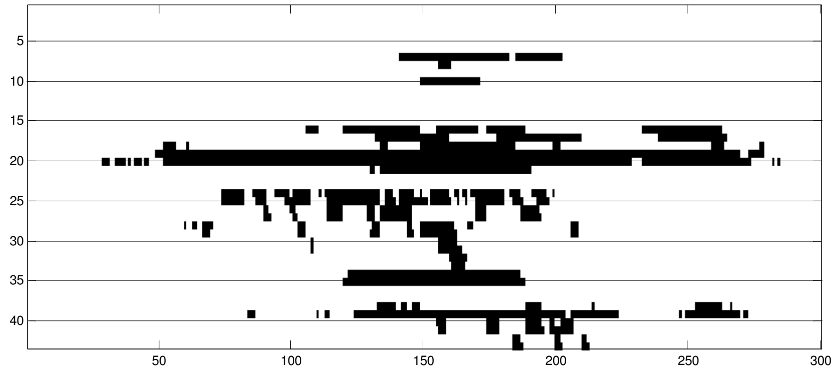


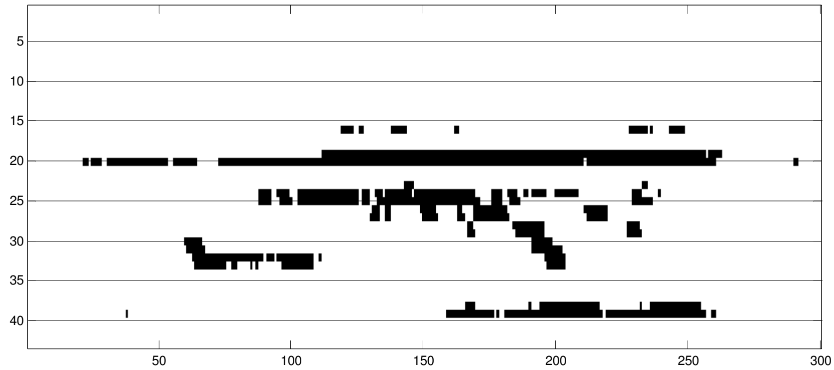


Hoevelaken a.m. peak – Tuesdays (1st, 8th, 15th, 22nd of May 2001).

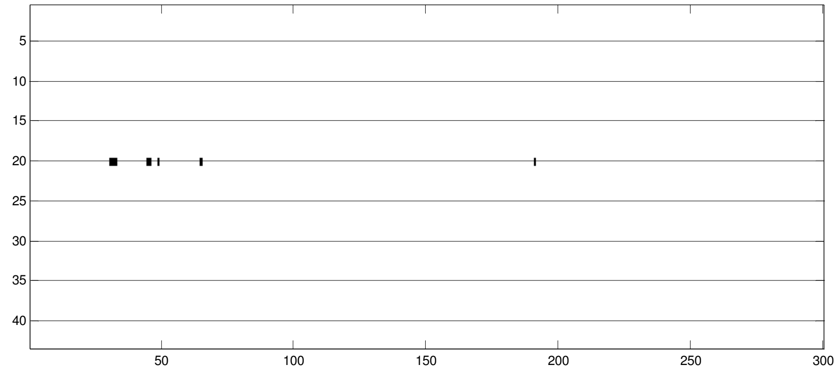


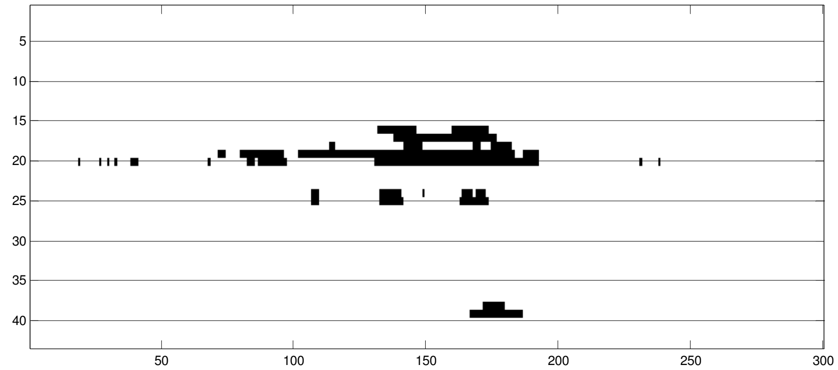


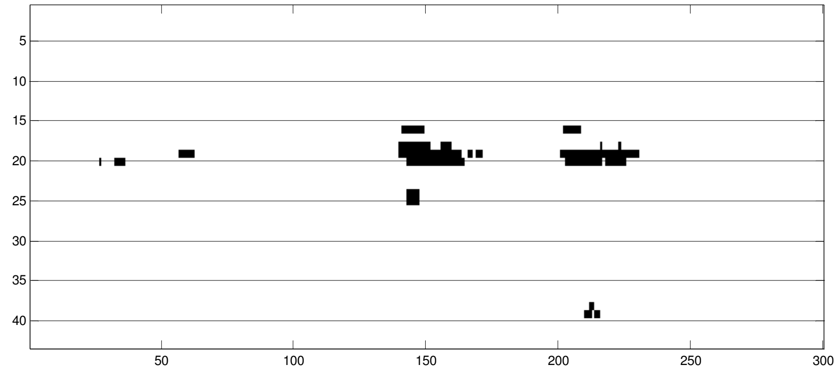


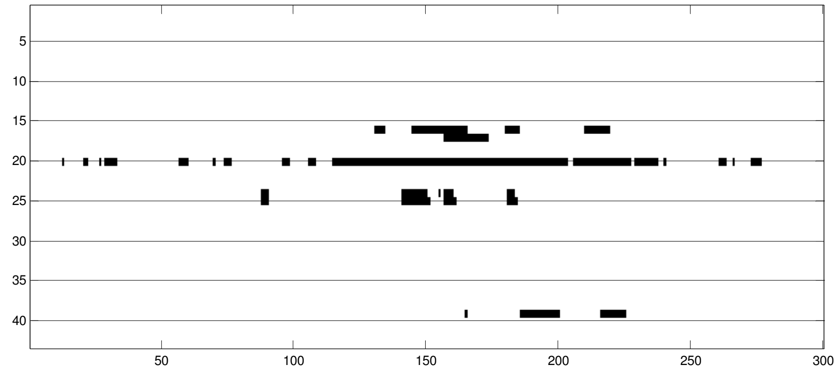


Hoevelaken a.m. peak – Wednesdays (2nd, 9th, 16th, 30th of May 2001).

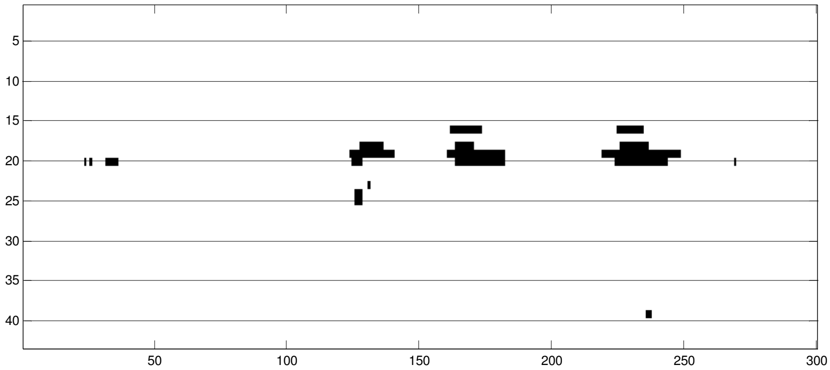


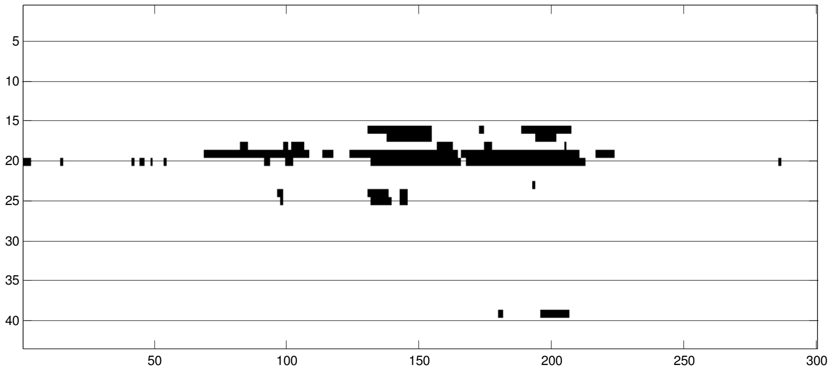


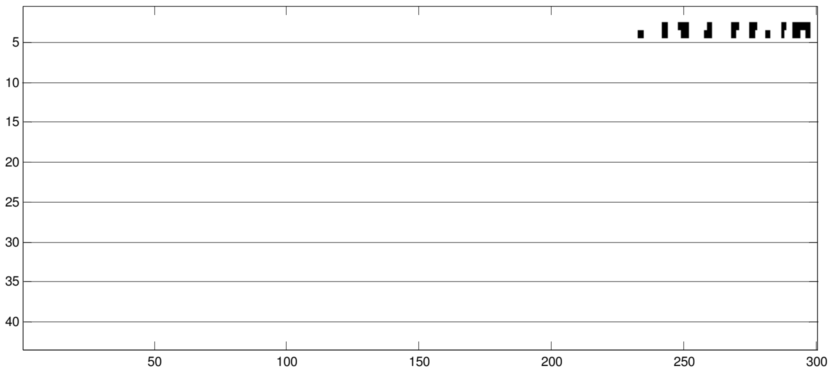


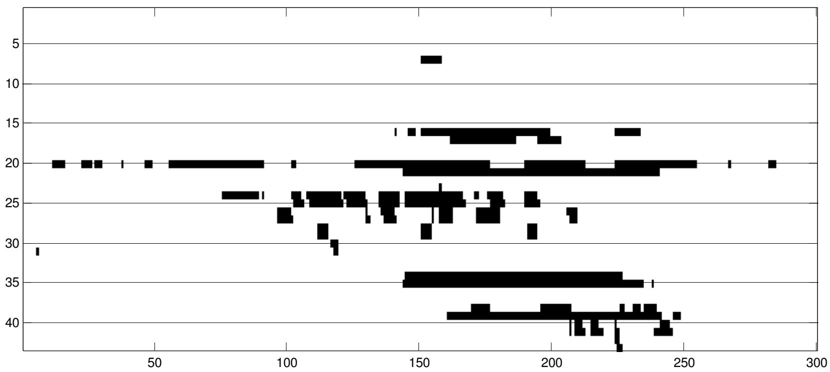


Hoevelaken a.m. peak – Thursdays (3rd, 17th, 24th, 31st of May 2001).

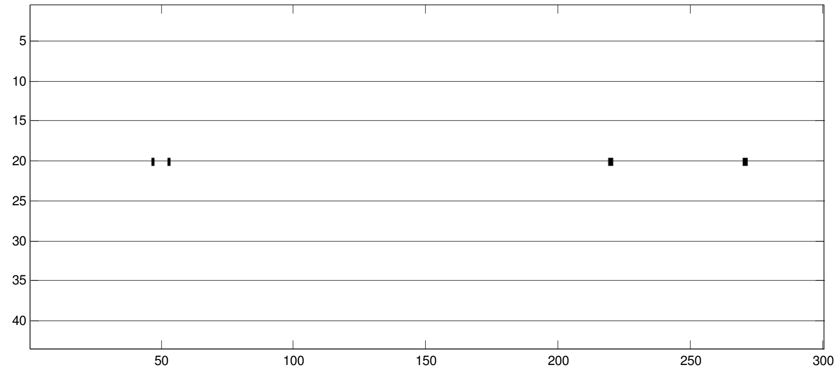


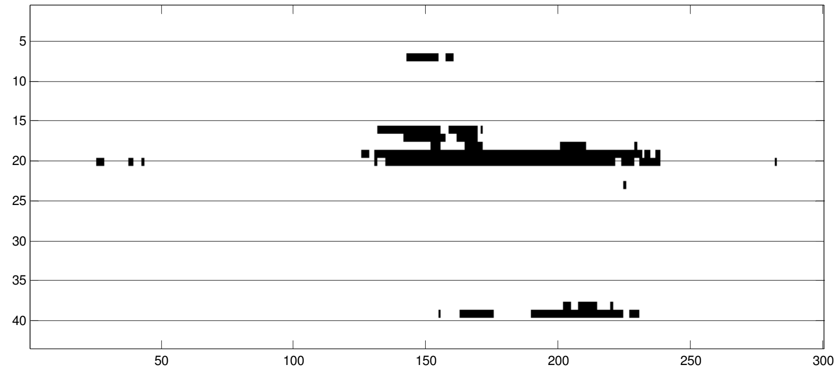


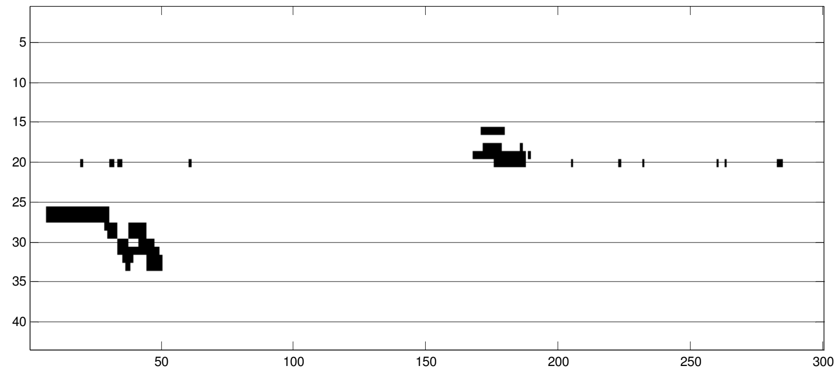


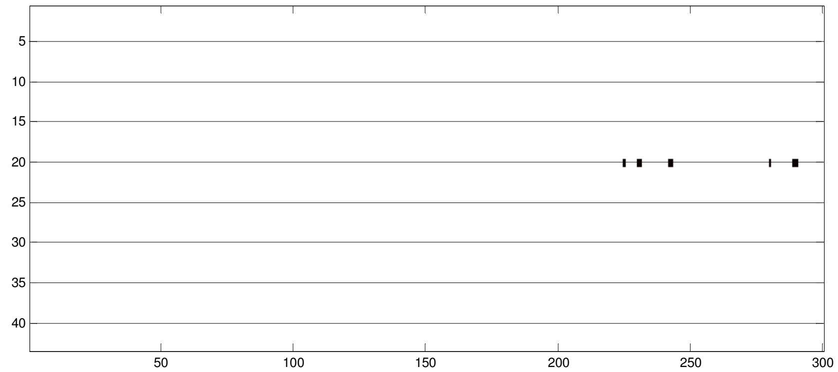


Hoevelaken a.m. peak – Fridays (4th, 11th, 18th, 25th of May 2001).







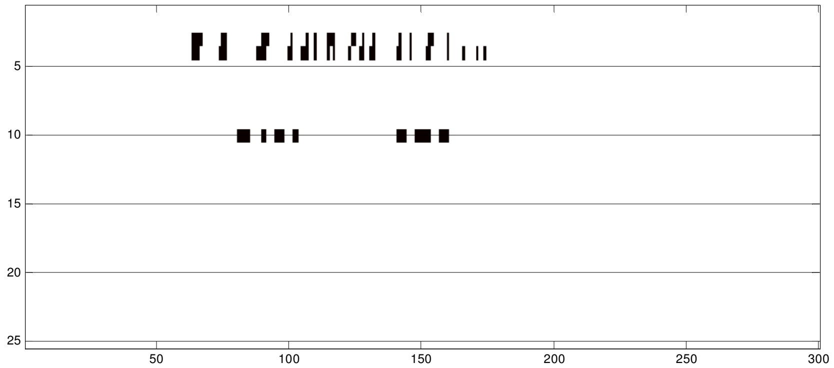


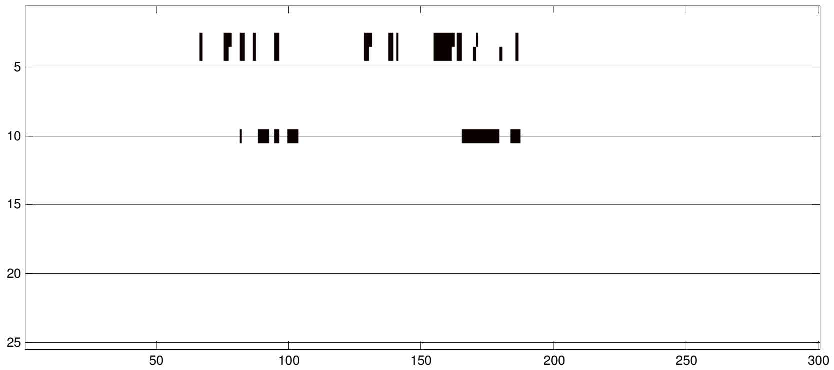
APPENDIX

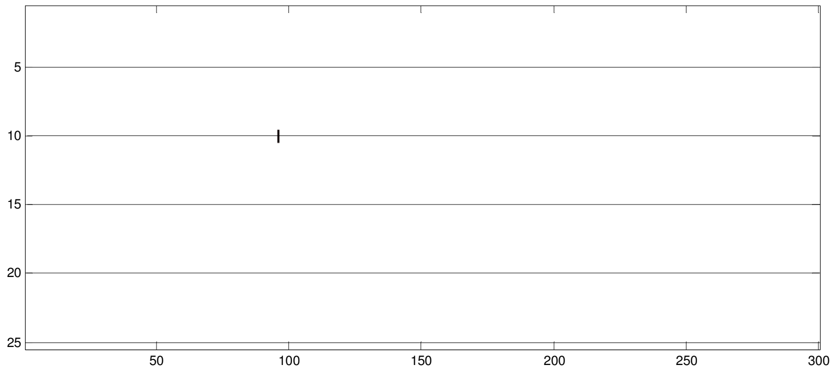
I

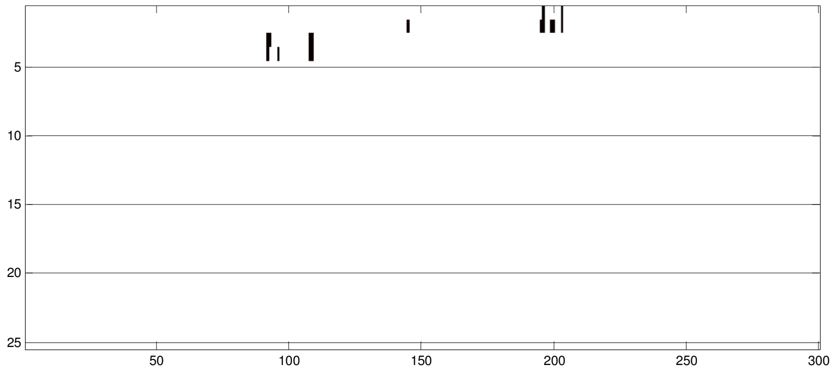
Congestion graphs – Hoevelaken evening peak

Hoevelaken p.m. peak – Mondays (7th, 14th, 21st, 28th of May 2001).

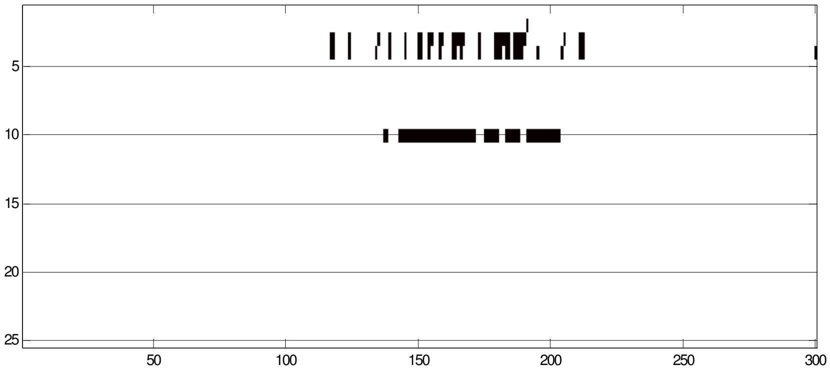


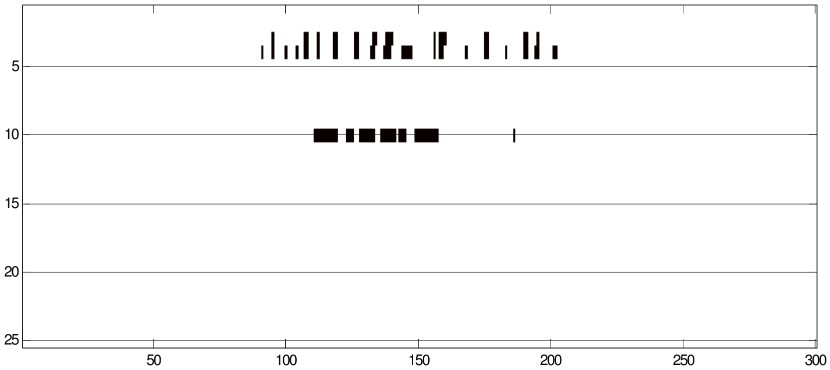


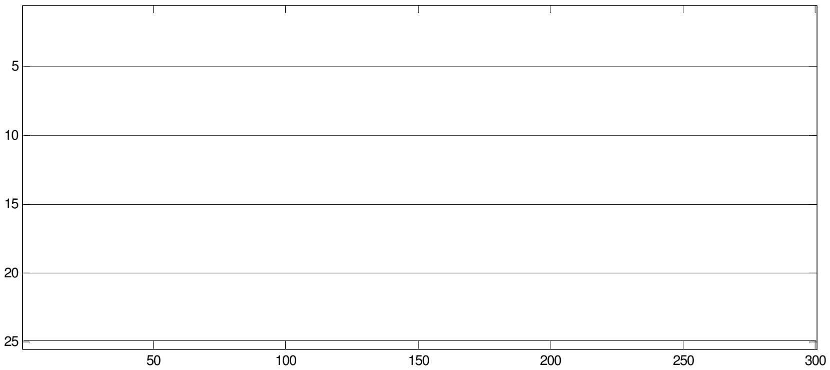


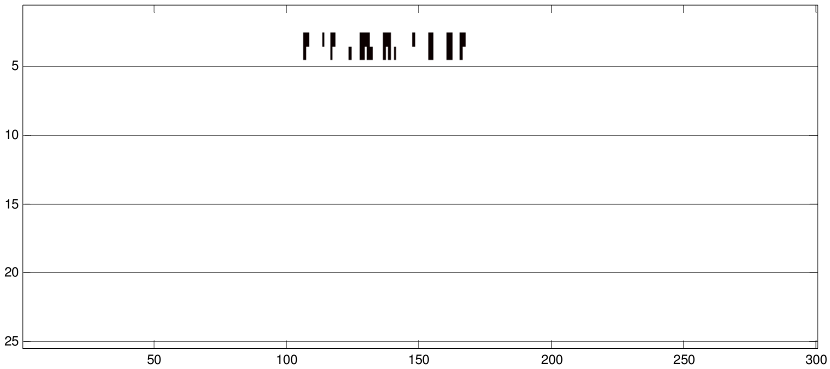


Hoevelaken p.m. peak – Tuesdays (1st, 8th, 15th, 22nd of May 2001).

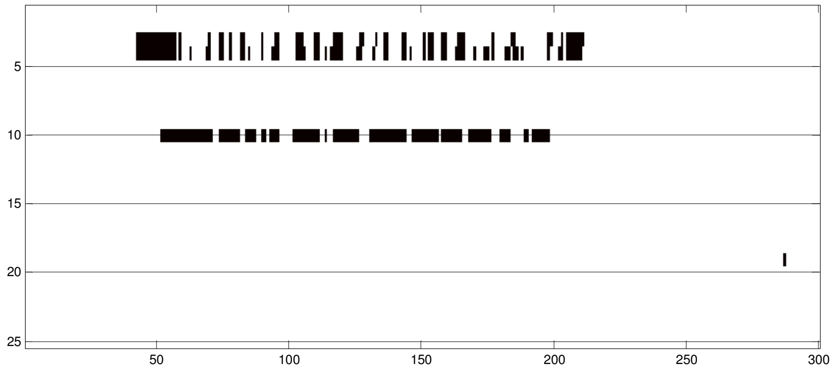


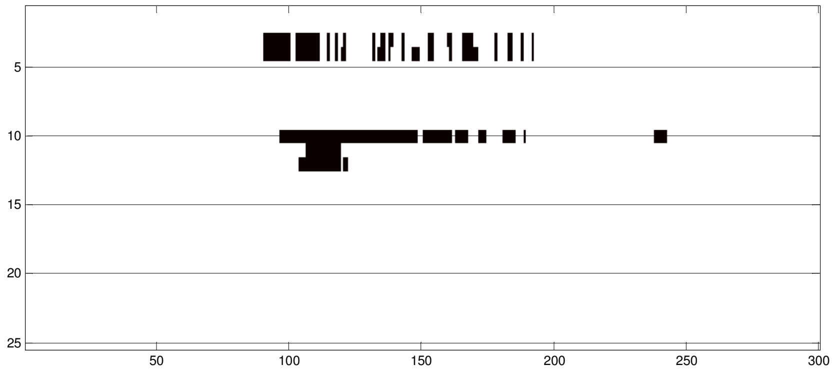


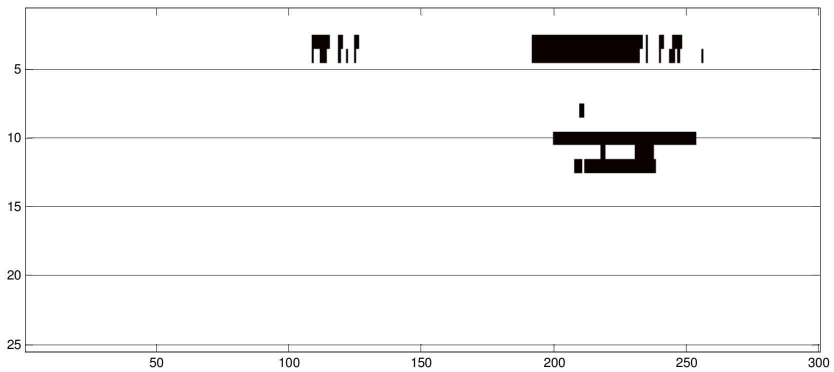


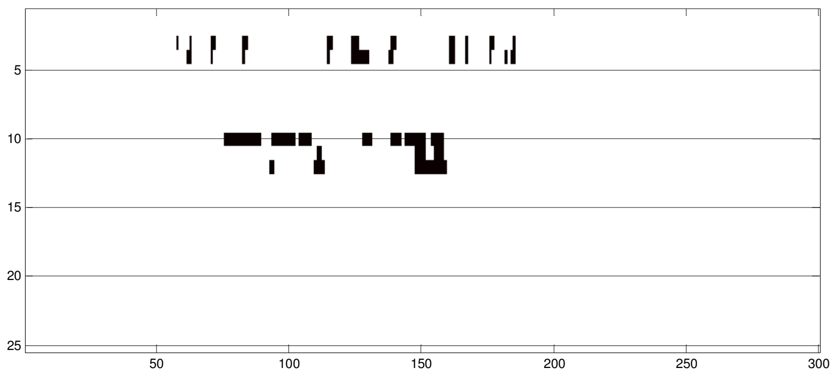


Hoevelaken p.m. peak – Wednesdays (2nd, 9th, 16th, 30th of May 2001).

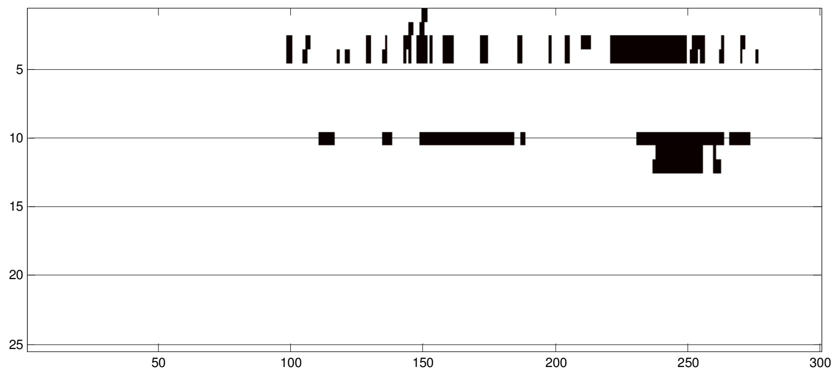


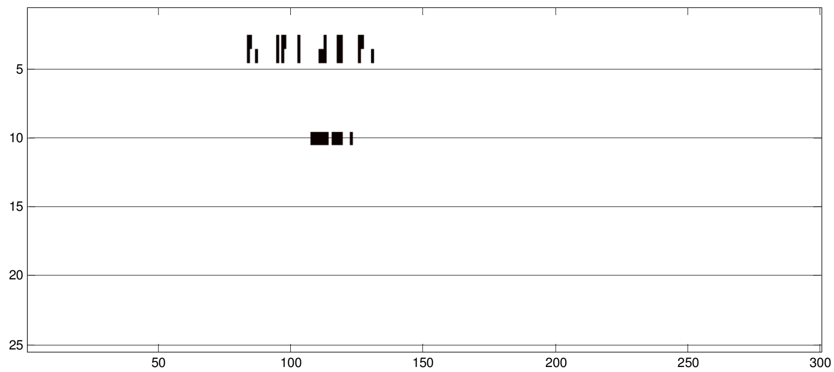


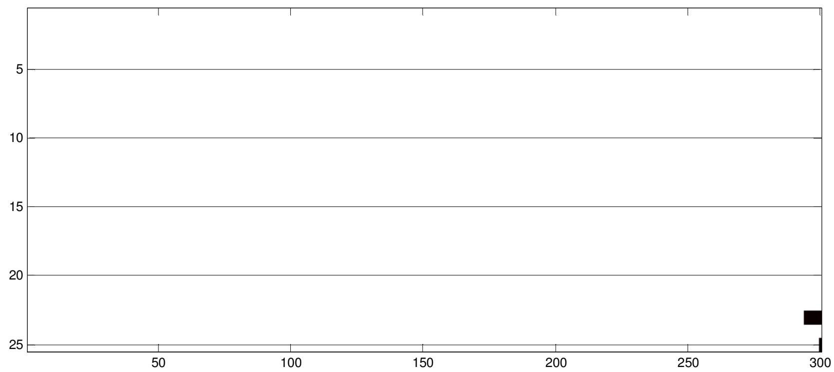


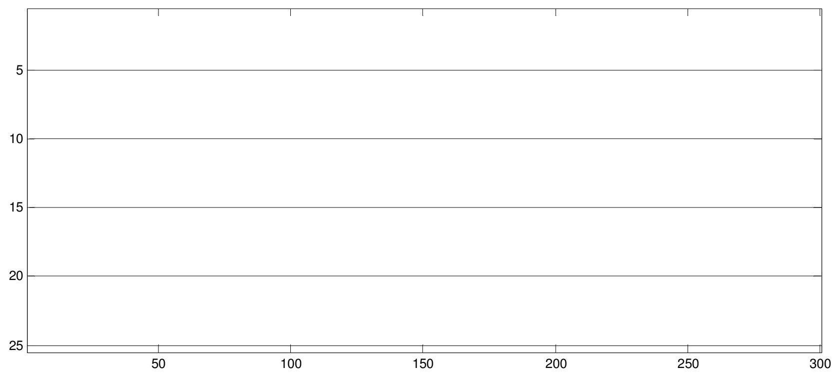


Hoevelaken p.m. peak – Thursdays (3rd, 17th, 24th, 31st of May 2001).

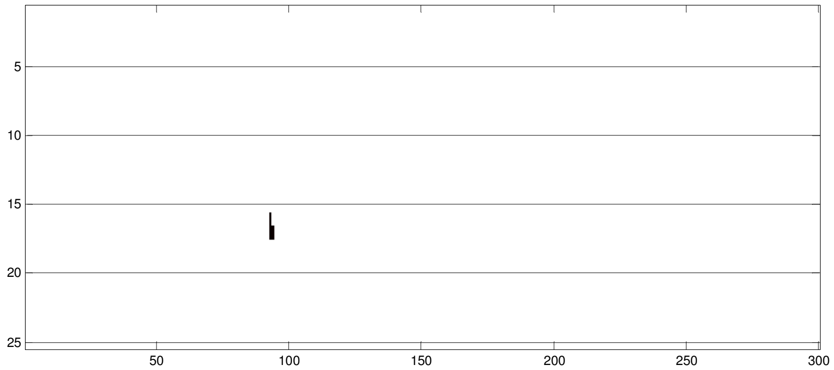


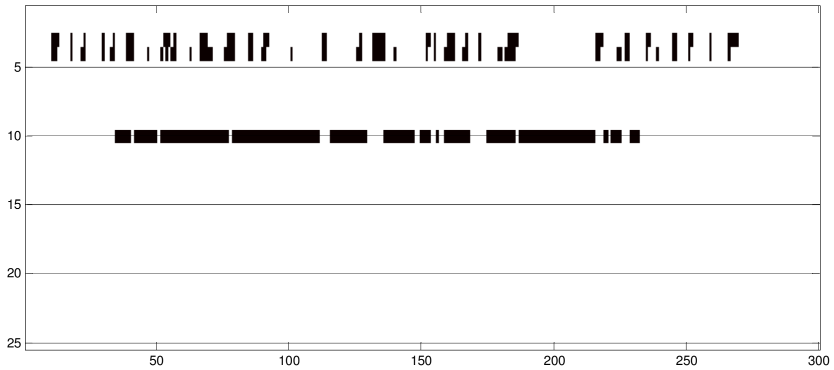


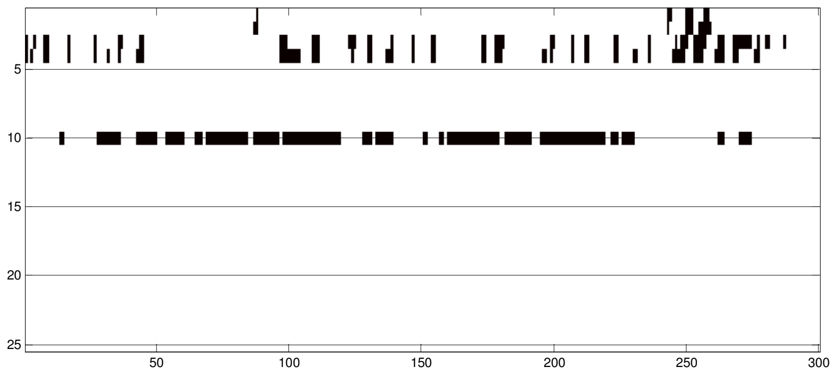


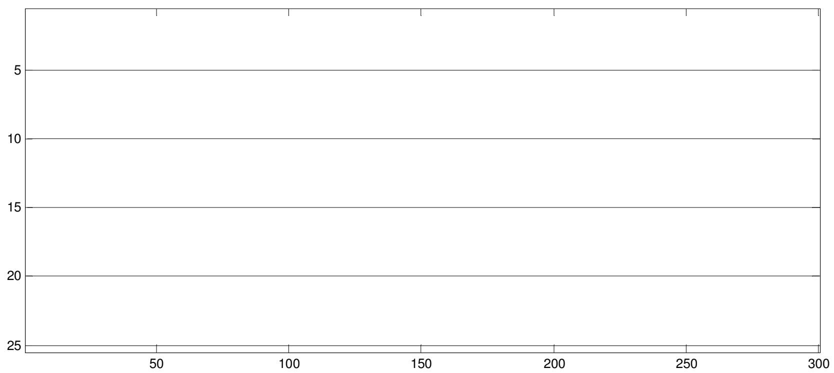


Hoevelaken p.m. peak – Fridays (4th, 11th, 18th, 25th of May 2001).









APPENDIX

J

Detector number coupling

Detector number coupling table							
Beekbergen				Hoevelaken			
Morning peak		Evening peak		Morning peak		Evening peak	
Rank	Origin	Rank	Origin	Rank	Origin	Rank	Origin
1	96	1	66	1	28	1	28 (11)
2	95	2	65	2	27	2	27 (10)
3	92	3	64	3	22	**3**	**22** (9)
4	91	4	63	4	21	4	21 (8)
5	90	5	60	5	18	5	18 (7)
6	89	6	59	6	17	6	17 (6)
7	88	7	56	7	16	7	16 (5)
8	1	8	54	8	13	8	13 (4)
9	2	9	53	9	12	9	12 (3)
10	3	10	50	10	29	10	29 (12)
11	4	11	48	11	9	11	9
12	9	12	47	12	8	12	8
13	10	13	41	13	4	13	4 (2)
14	11	14	40	14	3	14	3 (1)
15	12	15	39 (21)	15	30	15	30 (13)
16	16	16	38 (20)	16	2 (2)	16	35 (14)
17	17	17	35	17	1 (1)	17	36 (15)
18	20	18	32 (19)	18	31 (10)	18	41 (16)
19	21	19	31 (18)	19	32 (11)	19	42 (17)
20	25	20	30 (17)	**20**	**7** (3)	20	45 (18)
21	26	21	27 (16)	21	33	21	46 (19)
22	28	22	24 (13)	22	35 (12)	22	51 (20)
23	29	**23**	**23** (12)	23	36 (13)	23	52 (21)
24	33	24	22 (10)	24	37 (14)	24	55 (22)
25	34	25	78 (14)	25	38 (15)	25	56 (23)
26	36	26	19 (9)	26	41 (16)		
27	37	27	18 (8)	27	42 (17)		
28	42 (14)	28	14 (6)	28	45 (18)		
29	43 (15)	29	13 (5)	29	46 (19)		
30	44 (1)	30	71 (11)	30	51 (20)		
31	**45** (2)	31	77 (7)	31	52 (21)		
32	46 (3)	32	8 (4)	32	55 (22)		
33	49 (4)	33	7 (3)	33	56 (23)		
34	51 (5)	34	6 (2)	34	5		
35	52 (6)	35	5 (1)	35	6		
36	55 (7)	36	82 (15)	36	14		
37	57 (8)	37	85	37	15		
38	58 (9)	38	86	38	19 (4)		
39	61 (10)	39	87	39	20 (5)		
40	62 (11)	40	93	40	23 (6)		
41	67 (12)	41	94	41	24 (7)		
42	68 (13)			42	25 (8)		
				43	26 (9)		

The detector number coupling table provides the linkage between original ranks of the detector (as originally provided) and the new ranks as they are used in appendices F – I. The numbers displayed in bold are the detectors that were identified as bottleneck detectors. The numbers between brackets give the final rank in the selection of detectors that serve as input for the methods (see 6.3).

APPENDIX

K

Result tables

BB - AM - RESULTS

	gap 0 min			1 min			2 min			3 min			4 min			5 min		
horizon																		
	Naive																	
0 min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5 min	3.417	3.417	6.833	3.183	3.183	6.367	2.683	2.683	5.367	2.117	2.117	4.233	1.867	1.867	3.733	1.450	1.450	2.900
10 min	4.217	4.217	8.433	3.917	3.917	7.833	3.517	3.517	7.033	3.067	3.067	6.133	2.950	2.950	5.900	2.683	2.683	5.367
15 min	4.950	4.950	9.900	4.783	4.783	9.567	4.483	4.483	8.967	4.000	4.000	8.000	3.967	3.967	7.933	3.700	3.700	7.400
20 min	5.667	5.667	11.333	5.550	5.550	11.100	5.250	5.250	10.500	4.867	4.867	9.733	4.883	4.883	9.767	4.633	4.633	9.267
25 min	6.467	6.467	12.933	6.300	6.300	12.600	6.067	6.067	12.133	5.817	5.817	11.633	5.817	5.817	11.633	5.667	5.667	11.333
30 min	7.317	7.317	14.633	7.283	7.283	14.567	7.200	7.200	14.400	6.783	6.783	13.567	6.783	6.783	13.567	6.750	6.750	13.500
			64.067			62.033			58.400			53.300			52.533			49.767
	MLR																	
0 min	0.317	2.050	2.367	0.200	1.867	2.067	0.133	1.733	1.867	0.133	1.433	1.567	0.200	1.367	1.567	0.200	0.950	1.150
5 min	1.783	3.383	5.167	1.650	3.100	4.750	1.433	2.650	4.083	1.217	2.083	3.300	1.233	1.767	3.000	1.100	1.383	2.483
10 min	2.850	3.750	6.600	2.617	3.433	6.050	2.383	3.033	5.417	2.350	2.650	5.000	2.417	2.650	5.067	2.500	2.317	4.817
15 min	3.533	4.300	7.833	3.317	4.117	7.433	3.217	3.950	7.167	3.233	3.567	6.800	3.150	3.483	6.633	3.300	3.300	6.600
20 min	4.500	4.567	9.067	4.033	4.533	8.567	3.817	4.283	8.100	3.967	3.933	7.900	3.833	3.800	7.633	3.900	3.533	7.433
25 min	5.700	4.833	10.533	5.167	4.967	10.133	4.950	4.850	9.800	4.900	4.650	9.550	4.833	4.650	9.483	4.717	4.450	9.167
30 min	6.633	5.100	11.733	5.867	5.400	11.267	5.517	5.250	10.767	5.317	5.150	10.467	5.250	5.350	10.600	5.250	5.183	10.433
			50.933			48.200			45.333			43.017			42.417			40.933
	ARMA																	
0 min	3.600	1.400	5.000	3.617	1.150	4.767	3.350	0.883	4.233	3.350	0.433	3.783	3.267	0.417	3.683	3.583	0.400	3.983
5 min	5.633	2.733	8.367	5.533	2.433	7.967	5.317	2.117	7.433	5.183	1.533	6.717	5.100	1.383	6.483	5.233	1.267	6.500
10 min	6.667	3.133	9.800	6.567	2.833	9.400	6.250	2.550	8.800	6.217	2.117	8.333	6.167	2.067	8.233	5.867	1.850	7.717
15 min	7.383	3.233	10.617	7.400	2.967	10.367	7.283	2.717	10.000	7.333	2.417	9.750	7.400	2.283	9.683	7.500	2.050	9.550
20 min	8.450	3.600	12.050	8.433	3.383	11.817	8.250	3.067	11.317	8.100	2.917	11.017	8.183	2.867	11.050	8.283	2.717	11.000
25 min	9.217	3.550	12.767	9.317	3.483	12.800	9.267	3.267	12.533	9.200	3.000	12.200	9.167	2.833	12.000	9.000	2.750	11.750
30 min	10.600	3.883	14.483	10.78	3.833	14.617	10.78	3.633	14.417	10.70	3.450	14.150	10.883	3.500	14.383	11.03	3.567	14.600
			68.083			66.967			64.500			62.167			61.833			61.117
	MLF	6 - 30 epochs																
0 min	0.683	1.150	1.833	0.383	1.217	1.600	0.300	1.233	1.533	0.100	0.983	1.083	0.167	1.050	1.217	0.167	0.717	0.883
5 min	1.733	3.500	5.233	1.483	3.250	4.733	1.267	2.800	4.067	1.083	2.217	3.300	1.067	2.067	3.133	0.917	1.833	2.750
10 min	2.617	3.700	6.317	2.300	3.500	5.800	1.933	3.167	5.100	1.633	2.717	4.350	1.700	2.583	4.283	1.550	2.267	3.817
15 min	2.767	4.667	7.433	2.333	4.450	6.783	2.017	4.233	6.250	1.733	3.850	5.583	1.583	3.633	5.217	1.050	3.433	4.483
20 min	3.083	4.783	7.867	2.450	4.767	7.217	2.117	4.700	6.817	1.967	4.350	6.317	1.683	4.267	5.950	1.433	4.017	5.450
25 min	4.583	5.267	9.850	3.600	5.300	8.900	3.000	5.367	8.367	2.633	4.800	7.433	2.267	4.833	7.100	2.000	5.150	7.150
30 min	5.533	5.200	10.733	4.517	5.467	9.983	3.400	5.450	8.850	3.100	5.150	8.250	2.883	5.667	8.550	2.850	5.717	8.567
			47.433			43.417			39.450			35.233			34.233			32.217
	RBF	6 - 70 epochs																
0 min	1.000	1.417	2.417	0.517	1.483	2.000	0.367	1.367	1.733	0.167	1.267	1.433	0.233	1.200	1.433	0.233	0.783	1.017
5 min	2.367	3.183	5.550	1.800	2.933	4.733	1.550	2.550	4.100	1.200	1.950	3.150	0.983	1.733	2.717	1.033	1.367	2.400
10 min	2.717	3.400	6.117	2.417	3.617	6.033	1.917	3.183	5.100	1.767	2.683	4.450	1.683	2.533	4.217	1.533	2.133	3.667
15 min	3.483	4.467	7.950	2.500	4.350	6.850	2.050	4.167	6.217	1.933	3.800	5.733	1.683	3.617	5.300	1.450	3.467	4.917
20 min	4.233	4.583	8.817	3.033	4.700	7.733	2.133	4.467	6.600	1.667	4.550	6.217	1.567	4.317	5.883	1.567	4.150	5.717
25 min	5.500	4.683	10.183	4.000	5.167	9.167	3.100	5.133	8.233	2.667	5.000	7.667	2.450	5.050	7.500	2.483	5.167	7.650
30 min	6.217	5.583	11.800	4.717	5.833	10.550	3.783	6.100	9.883	3.250	6.117	9.367	2.983	6.183	9.167	2.967	6.583	9.550
			50.417			45.067			40.133			36.583			34.783			33.900

	ELM	6 - 200 epochs																
0 min	0.633	1.983	2.617	0.283	1.900	2.183	0.183	1.867	2.050	0.133	1.517	1.650	0.133	1.517	1.650	0.217	1.183	1.400
5 min	2.117	3.367	5.483	1.717	3.083	4.800	1.517	2.717	4.233	1.367	2.067	3.433	1.200	1.833	3.033	1.117	1.500	2.617
10 min	2.650	3.617	6.267	2.283	3.350	5.633	2.117	3.017	5.133	2.050	2.500	4.550	1.850	2.500	4.350	1.833	2.150	3.983
15 min	3.333	4.050	7.383	2.717	3.833	6.550	2.417	3.467	5.883	2.250	3.000	5.250	2.150	3.100	5.250	2.133	2.833	4.967
20 min	3.617	4.617	8.233	2.767	4.800	7.567	2.517	4.583	7.100	2.317	4.283	6.600	2.050	4.083	6.133	1.967	4.083	6.050
25 min	4.733	5.267	10.000	3.700	5.483	9.183	3.150	5.367	8.517	2.833	5.000	7.833	2.633	5.000	7.633	2.433	5.133	7.567
30 min	5.783	5.267	11.050	4.600	5.583	10.183	3.800	5.550	9.350	3.367	5.267	8.633	2.967	5.333	8.300	2.883	5.167	8.050
			48.417			43.917			40.217			36.300			34.700			33.233
	SOM																	
0 min	0.517	9.717	10.233	0.500	10.100	10.600	0.400	10.667	11.067	0.400	11.117	11.517	0.367	11.817	12.183	0.283	12.067	12.350
5 min	0.817	10.017	10.833	0.767	10.367	11.133	0.617	10.883	11.500	0.433	11.150	11.583	0.333	11.783	12.117	0.333	12.117	12.450
10 min	1.133	10.333	11.467	1.000	10.600	11.600	0.950	11.217	12.167	0.767	11.483	12.250	0.633	12.083	12.717	0.667	12.450	13.117
15 min	1.600	10.800	12.400	1.417	11.017	12.433	1.350	11.617	12.967	1.233	11.950	13.183	1.200	12.650	13.850	1.267	13.050	14.317
20 min	2.317	11.517	13.833	2.083	11.683	13.767	2.067	12.333	14.400	1.933	12.650	14.583	1.850	13.300	15.150	1.933	13.717	15.650
25 min	3.117	12.317	15.433	2.850	12.450	15.300	2.783	13.050	15.833	2.533	13.250	15.783	2.500	13.950	16.450	2.583	14.367	16.950
30 min	3.900	13.100	17.000	3.700	13.300	17.000	3.683	13.950	17.633	3.433	14.150	17.583	3.233	14.683	17.917	3.300	15.083	18.383
			80.967			81.233			84.500			84.967			88.200			90.867
	FL	125 epochs																
0 min	1.633	2.067	3.700	0.883	2.133	3.017	0.383	1.933	2.317	0.367	1.567	1.933	0.233	1.700	1.933	0.283	1.600	1.883
5 min	2.683	4.350	7.033	1.950	4.233	6.183	1.333	3.867	5.200	1.133	3.300	4.433	0.883	3.133	4.017	0.883	2.800	3.683
10 min	3.683	5.000	8.683	2.500	5.150	7.650	2.117	4.967	7.083	1.717	4.533	6.250	1.750	4.567	6.317	1.833	4.233	6.067
15 min	4.433	5.700	10.133	3.500	5.800	9.300	3.017	5.883	8.900	2.900	5.383	8.283	2.800	5.283	8.083	2.950	5.100	8.050
20 min	6.017	5.867	11.883	4.950	6.017	10.967	4.417	6.067	10.483	4.183	5.967	10.150	3.850	5.900	9.750	3.933	5.733	9.667
25 min	7.617	5.300	12.917	6.450	5.883	12.333	5.733	5.867	11.600	5.417	5.867	11.283	5.033	6.017	11.050	5.050	6.117	11.167
30 min	8.700	5.950	14.650	7.317	6.433	13.750	6.367	6.850	13.217	6.133	6.933	13.067	5.983	7.050	13.033	5.900	7.050	12.950
			65.300			60.183			56.483			53.467			52.250			51.583

BB - PM - RESULTS

gap / **horizon**	0 min			1 min			2 min			3 min			4 min			5 min		
Naive																		
0 min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5 min	5.383	5.383	10.767	5.400	5.400	10.800	5.283	5.283	10.567	5.033	5.033	10.067	4.517	4.517	9.033	3.867	3.867	7.733
10 min	5.783	5.783	11.567	5.750	5.750	11.500	5.650	5.650	11.300	5.467	5.467	10.933	5.383	5.383	10.767	5.450	5.450	10.900
15 min	6.400	6.400	12.800	6.400	6.400	12.800	6.317	6.317	12.633	6.067	6.067	12.133	5.983	5.983	11.967	6.200	6.200	12.400
20 min	7.000	7.000	14.000	7.050	7.050	14.100	7.067	7.067	14.133	7.133	7.133	14.267	7.083	7.083	14.167	7.167	7.167	14.333
25 min	7.200	7.200	14.400	7.167	7.167	14.333	7.200	7.200	14.400	7.467	7.467	14.933	7.750	7.750	15.500	8.083	8.083	16.167
30 min	7.800	7.800	15.600	7.850	7.850	15.700	7.933	7.933	15.867	8.383	8.383	16.767	8.583	8.583	17.167	9.000	9.000	18.000
			79.133			79.233			78.900			79.100			78.600			79.533
MLR																		
0 min	2.883	1.767	4.650	2.450	1.900	4.350	2.133	2.083	4.217	2.200	2.250	4.450	1.583	2.500	4.083	1.650	2.983	4.633
5 min	6.617	3.150	9.767	5.967	3.300	9.267	5.683	3.383	9.067	5.917	2.917	8.833	6.250	2.650	8.900	6.833	2.817	9.650
10 min	8.583	3.150	11.733	8.217	3.367	11.583	8.267	3.550	11.817	8.667	3.300	11.967	8.933	3.167	12.100	9.150	3.133	12.283
15 min	10.583	2.433	13.017	10.28	2.667	12.950	10.17	2.750	12.917	10.43	2.567	13.000	10.783	2.383	13.167	11.37	2.467	13.833
20 min	10.017	2.417	12.433	9.567	2.650	12.217	9.533	2.950	12.483	10.17	2.733	12.900	10.367	2.733	13.100	10.90	2.683	13.583
25 min	10.950	2.150	13.100	10.77	2.433	13.200	10.77	2.567	13.333	11.52	2.567	14.083	11.967	2.483	14.450	12.52	2.533	15.050
30 min	10.983	2.250	13.233	10.62	2.383	13.000	10.78	2.417	13.200	11.65	2.283	13.933	12.267	2.700	14.967	12.80	2.650	15.450
			73.283			72.217			72.817			74.717			76.683			79.850
ARMA																		
0 min	1.683	1.483	3.167	1.450	1.550	3.000	1.317	1.717	3.033	1.567	2.117	3.683	1.167	1.850	3.017	0.900	2.167	3.067
5 min	8.667	3.417	12.083	8.317	3.600	11.917	8.383	3.533	11.917	8.817	3.267	12.083	9.267	2.783	12.050	9.583	2.433	12.017
10 min	10.083	3.150	13.233	9.783	3.233	13.017	9.800	3.217	13.017	10.53	2.950	13.483	11.000	2.750	13.750	11.58	2.667	14.250
15 min	11.667	2.483	14.150	11.68	2.617	14.300	11.90	2.667	14.567	12.80	2.567	15.367	13.267	2.500	15.767	13.80	2.450	16.250
20 min	12.833	1.983	14.817	12.85	2.083	14.933	13.17	2.133	15.300	14.17	2.233	16.400	14.883	2.217	17.100	15.33	2.083	17.417
25 min	13.133	1.883	15.017	13.17	1.950	15.117	13.47	2.017	15.483	14.55	2.000	16.550	15.300	1.950	17.250	16.03	1.933	17.967
30 min	13.750	1.367	15.117	13.87	1.450	15.317	14.25	1.500	15.750	15.28	1.433	16.717	16.150	1.433	17.583	16.92	1.700	18.617
			84.417			84.600			86.033			90.600			93.500			96.517
MLF	6 - 10 epochs																	
0 min	1.883	2.400	4.283	1.800	2.683	4.483	1.633	3.150	4.783	1.683	2.900	4.583	1.400	2.950	4.350	1.700	3.250	4.950
5 min	5.050	3.383	8.433	4.633	3.683	8.317	4.600	3.617	8.217	4.867	3.133	8.000	5.150	2.883	8.033	5.750	2.733	8.483
10 min	6.050	4.383	10.433	7.133	3.533	10.667	6.833	3.600	10.433	7.100	3.117	10.217	7.533	2.950	10.483	8.267	3.100	11.367
15 min	6.133	4.467	10.600	7.450	3.883	11.333	7.283	4.017	11.300	7.433	3.717	11.150	7.533	3.283	10.817	8.017	3.267	11.283
20 min	6.483	4.817	11.300	7.100	3.650	10.750	7.033	3.817	10.850	7.400	3.533	10.933	7.783	3.250	11.033	8.400	3.450	11.850
25 min	7.033	5.367	12.400	7.550	3.050	10.600	7.483	3.250	10.733	7.833	3.000	10.833	8.117	2.683	10.800	8.583	2.650	11.233
30 min	7.100	5.433	12.533	8.017	2.567	10.583	7.817	2.700	10.517	8.500	2.533	11.033	8.967	2.467	11.433	9.483	2.567	12.050
			65.700			62.250			62.050			62.167			62.600			66.267
RBF	6 - 70 epochs																	
0 min	4.167	2.117	6.283	3.433	2.350	5.783	2.850	2.767	5.617	2.783	3.067	5.850	2.117	3.467	5.583	2.317	3.667	5.983
5 min	8.233	2.400	10.633	7.383	2.600	9.983	6.600	2.750	9.350	6.167	2.517	8.683	5.967	2.317	8.283	6.517	2.367	8.883
10 min	8.750	2.917	11.667	8.750	3.017	11.767	8.367	3.200	11.567	8.500	3.133	11.633	8.567	3.200	11.767	8.717	3.183	11.900
15 min	8.883	3.050	11.933	9.550	2.450	12.000	9.367	2.667	12.033	9.933	2.483	12.417	10.083	2.300	12.383	10.67	2.333	12.950
20 min	9.083	3.250	12.333	9.667	2.233	11.900	9.333	2.467	11.800	9.517	2.300	11.817	9.617	2.267	11.883	10.00	2.233	12.233
25 min	9.383	3.550	12.933	11.98	1.650	13.633	12.05	1.817	13.867	12.72	1.783	14.500	13.267	1.600	14.867	14.00	1.500	15.500
30 min	9.217	3.383	12.600	11.22	1.650	12.867	11.15	1.883	13.033	11.75	1.683	13.433	12.017	1.483	13.500	12.52	1.483	14.000
			72.100			72.150			71.650			72.483			72.683			75.467

	ELM	6 - 200 epochs																
0 min	2.583	1.333	3.917	2.300	1.533	3.833	1.983	1.883	3.867	2.017	1.767	3.783	1.633	1.850	3.483	1.900	1.950	3.850
5 min	6.917	2.650	9.567	6.250	2.817	9.067	6.000	3.000	9.000	6.517	2.867	9.383	6.367	2.650	9.017	6.733	2.767	9.500
10 min	8.167	3.900	12.067	6.000	4.233	10.233	5.667	4.467	10.133	6.150	3.950	10.100	6.217	3.950	10.167	6.567	3.883	10.450
15 min	8.033	3.767	11.800	8.700	2.717	11.417	8.633	2.883	11.517	9.183	2.683	11.867	9.700	2.600	12.300	10.30	2.700	13.000
20 min	8.317	4.050	12.367	6.967	3.633	10.600	6.867	3.700	10.567	7.300	3.433	10.733	7.750	3.350	11.100	8.233	3.333	11.567
25 min	8.600	4.333	12.933	8.767	2.517	11.283	8.533	2.550	11.083	9.183	2.350	11.533	9.450	2.417	11.867	9.917	2.383	12.300
30 min	8.833	4.567	13.400	6.717	3.650	10.367	6.550	3.783	10.333	7.217	3.600	10.817	7.517	3.633	11.150	8.183	3.467	11.650
			72.133			62.967			62.633			64.433			65.600			68.467
	SOM																	
0 min	10.100	16.350	26.450	9.617	19.233	28.850	9.283	22.267	31.550	9.367	25.100	34.467	9.433	27.700	37.133	9.550	29.317	38.867
5 min	10.550	16.800	27.350	10.13	19.750	29.883	9.800	22.783	32.583	9.883	25.617	35.500	9.767	28.033	37.800	9.750	29.517	39.267
10 min	10.333	16.583	26.917	9.883	19.500	29.383	9.833	22.817	32.650	10.00	25.733	35.733	10.050	28.317	38.367	10.15	29.917	40.067
15 min	10.383	16.633	27.017	9.800	19.417	29.217	9.600	22.583	32.183	9.717	25.450	35.167	10.000	28.267	38.267	10.27	30.033	40.300
20 min	10.500	16.750	27.250	9.967	19.583	29.550	9.833	22.817	32.650	10.25	25.983	36.233	10.333	28.600	38.933	10.48	30.250	40.733
25 min	10.433	16.683	27.117	10.07	19.683	29.750	9.967	22.950	32.917	10.17	25.900	36.067	10.433	28.700	39.133	10.35	30.117	40.467
30 min	10.533	16.783	27.317	10.07	19.683	29.750	10.08	23.067	33.150	10.12	25.850	35.967	10.433	28.700	39.133	10.45	30.217	40.667
			162.967			177.53			196.13			214.67			231.63			241.50
	FL	125 epochs																
0 min	1.617	1.183	2.800	1.283	1.283	2.567	1.050	1.383	2.433	1.050	1.683	2.733	0.683	2.117	2.800	0.433	2.283	2.717
5 min	9.033	4.017	13.050	8.450	4.350	12.800	7.783	4.483	12.267	8.150	4.250	12.400	7.350	4.383	11.733	6.383	4.500	10.883
10 min	9.233	3.150	12.383	8.667	3.417	12.083	8.450	3.667	12.117	8.333	3.650	11.983	7.933	3.783	11.717	7.767	4.533	12.300
15 min	10.567	3.000	13.567	10.17	3.200	13.367	9.967	3.367	13.333	10.12	3.167	13.283	9.900	3.150	13.050	10.13	3.383	13.517
20 min	12.533	2.350	14.883	12.48	2.517	15.000	12.80	2.533	15.333	13.38	2.617	16.000	13.983	2.683	16.667	14.18	3.133	17.317
25 min	12.017	2.267	14.283	11.80	2.433	14.233	11.93	2.533	14.467	12.77	2.767	15.533	13.033	2.833	15.867	13.45	2.917	16.367
30 min	13.550	1.850	15.400	13.65	1.983	15.633	13.98	2.017	16.000	15.10	2.233	17.333	15.683	2.350	18.033	16.33	2.667	19.000
			83.567			83.117			83.517			86.533			87.067			89.383

	gap	0 min		1 min			2 min			3 min			4 min			5 min	
	HL - AM - RESULTS																	
horizon																		
	Naive																	
0 min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5 min	2.417	2.417	4.833	2.350	2.350	4.700	2.283	2.283	4.567	2.183	2.183	4.367	2.117	2.117	4.233	1.917	1.917	3.833
10 min	3.683	3.683	7.367	3.650	3.650	7.300	3.617	3.617	7.233	3.617	3.617	7.233	3.550	3.550	7.100	3.467	3.467	6.933
15 min	5.117	5.117	10.233	5.100	5.100	10.200	5.083	5.083	10.167	5.083	5.083	10.167	5.017	5.017	10.033	4.850	4.850	9.700
20 min	6.317	6.317	12.633	6.300	6.300	12.600	6.300	6.300	12.600	6.300	6.300	12.600	6.233	6.233	12.467	6.117	6.117	12.233
25 min	7.200	7.200	14.400	7.200	7.200	14.400	7.217	7.217	14.433	7.217	7.217	14.433	7.217	7.217	14.433	7.083	7.083	14.167
30 min	7.983	7.983	15.967	8.000	8.000	16.000	8.033	8.033	16.067	7.983	7.983	15.967	7.983	7.983	15.967	7.900	7.900	15.800
			65.433			65.200			65.067			64.767			64.233			62.667
	MLR																	
0 min	1.983	4.700	6.683	1.367	5.183	6.550	1.333	5.683	7.017	1.333	6.183	7.517	1.267	6.383	7.650	1.267	6.800	8.067
5 min	3.583	5.200	8.783	3.000	5.583	8.583	2.650	6.000	8.650	2.450	6.150	8.600	2.317	6.350	8.667	2.183	6.467	8.650
10 min	4.983	5.533	10.517	4.267	5.933	10.200	3.833	6.333	10.167	3.633	6.683	10.317	3.433	6.950	10.383	3.433	7.283	10.717
15 min	7.117	6.350	13.467	6.233	6.750	12.983	5.833	7.083	12.917	5.533	7.283	12.817	5.333	7.533	12.867	5.117	7.900	13.017
20 min	8.633	6.400	15.033	7.633	6.883	14.517	7.117	7.433	14.550	6.683	7.600	14.283	6.400	7.983	14.383	6.033	8.367	14.400
25 min	9.917	6.283	16.200	9.017	6.983	16.000	8.417	7.617	16.033	7.767	8.367	16.133	7.700	8.967	16.667	7.433	9.200	16.633
30 min	10.983	6.917	17.900	9.817	7.900	17.717	9.150	8.633	17.783	8.483	9.367	17.850	8.150	9.900	18.050	7.883	10.467	18.350
			81.900			80.000			80.100			80.000			81.017			81.767
	ARMA																	
0 min	0.950	2.083	3.033	0.933	2.150	3.083	0.867	2.283	3.150	0.867	2.283	3.150	0.850	2.267	3.117	0.767	2.433	3.200
5 min	4.583	2.667	7.250	4.483	2.633	7.117	4.333	2.583	6.917	4.183	2.433	6.617	3.917	2.500	6.417	3.717	2.300	6.017
10 min	6.033	3.567	9.600	5.900	3.567	9.467	5.633	3.467	9.100	5.517	3.450	8.967	5.517	3.450	8.967	5.517	3.283	8.800
15 min	7.667	4.683	12.350	7.450	4.700	12.150	7.317	4.700	12.017	7.250	4.633	11.883	7.183	4.633	11.817	6.800	4.583	11.383
20 min	9.100	5.750	14.850	8.867	5.767	14.633	8.700	5.700	14.400	8.633	5.683	14.317	8.500	5.683	14.183	8.550	5.567	14.117
25 min	10.233	6.500	16.733	9.983	6.567	16.550	9.817	6.767	16.583	9.700	6.650	16.350	9.633	6.717	16.350	9.450	6.617	16.067
30 min	11.317	6.833	18.150	11.22	7.100	18.317	11.18	7.200	18.383	11.08	7.150	18.233	11.017	7.150	18.167	10.93	7.150	18.083
			78.933			78.233			77.400			76.367			75.900			74.467
	MLF	6 - 50 epochs																
0 min	1.267	2.667	3.933	0.783	3.083	3.867	0.650	3.183	3.833	0.550	3.233	3.783	0.417	3.500	3.917	0.483	3.650	4.133
5 min	3.333	3.433	6.767	2.617	3.933	6.550	2.383	4.133	6.517	2.233	4.083	6.317	2.067	4.317	6.383	1.833	4.250	6.083
10 min	4.600	4.117	8.717	3.783	4.367	8.150	3.050	4.767	7.817	2.933	4.750	7.683	2.500	5.317	7.817	2.167	5.317	7.483
15 min	6.217	4.883	11.100	5.383	5.233	10.617	4.700	5.717	10.417	4.233	6.050	10.283	3.667	6.283	9.950	3.517	6.383	9.900
20 min	7.517	5.450	12.967	6.433	6.033	12.467	5.617	6.617	12.233	5.150	7.100	12.250	4.583	7.467	12.050	4.150	7.450	11.600
25 min	8.183	5.633	13.817	7.117	6.267	13.383	6.533	6.717	13.250	5.983	7.417	13.400	5.633	7.733	13.367	5.167	7.933	13.100
30 min	10.017	5.733	15.750	8.833	6.567	15.400	8.283	7.250	15.533	7.600	8.167	15.767	7.067	8.433	15.500	6.733	9.267	16.000
			69.117			66.567			65.767			65.700			65.067			64.167
	RBF	8 - 140 epochs																
0 min	1.567	3.167	4.733	1.050	3.533	4.583	1.033	3.967	5.000	0.983	4.317	5.300	0.917	4.450	5.367	1.067	4.767	5.833
5 min	2.933	5.050	7.983	2.533	5.533	8.067	2.300	6.067	8.367	2.133	6.500	8.633	2.017	6.917	8.933	1.917	7.317	9.233
10 min	4.583	6.183	10.767	3.833	6.783	10.617	3.383	7.267	10.650	3.183	7.867	11.050	2.983	8.400	11.383	2.983	8.567	11.550
15 min	6.667	6.017	12.683	5.783	6.550	12.333	5.317	7.183	12.500	4.917	7.433	12.350	4.533	7.917	12.450	4.200	8.000	12.200
20 min	8.800	4.900	13.700	7.850	5.383	13.233	6.817	5.983	12.800	6.150	6.367	12.517	5.483	7.167	12.650	5.150	7.167	12.317
25 min	10.050	4.900	14.950	8.867	5.400	14.267	7.667	6.133	13.800	7.117	6.483	13.600	6.750	6.783	13.533	6.367	7.233	13.600
30 min	12.483	5.117	17.600	11.05	5.867	16.917	10.27	6.517	16.783	9.517	7.417	16.933	9.383	7.883	17.267	9.083	8.833	17.917
			77.683			75.433			74.900			75.083			76.217			76.817

	ELM	12 - 800 epochs																
0 min	0.967	2.100	3.067	0.533	2.367	2.900	0.467	2.600	3.067	0.467	2.700	3.167	0.400	2.967	3.367	0.400	3.050	3.450
5 min	3.767	2.917	6.683	2.967	3.200	6.167	2.667	3.500	6.167	2.483	3.617	6.100	2.400	3.600	6.000	2.217	3.500	5.717
10 min	4.817	3.967	8.783	4.350	3.833	8.183	3.933	4.183	8.117	3.683	4.383	8.067	3.483	4.517	8.000	3.117	4.650	7.767
15 min	5.983	5.133	11.117	6.217	4.750	10.967	5.717	5.117	10.833	5.267	5.417	10.683	5.133	5.750	10.883	4.967	5.750	10.717
20 min	7.050	6.200	13.250	7.100	6.100	13.200	6.217	6.517	12.733	5.600	7.000	12.600	5.350	7.617	12.967	5.067	7.917	12.983
25 min	7.783	6.933	14.717	8.017	6.100	14.117	7.267	6.917	14.183	6.733	7.383	14.117	6.250	7.967	14.217	6.000	8.633	14.633
30 min	8.467	7.617	16.083	8.700	6.117	14.817	7.817	6.900	14.717	6.833	7.267	14.100	6.200	8.100	14.300	5.867	8.350	14.217
			70.633			67.450			66.750			65.667			66.367			66.033
	SOM																	
0 min	12.867	29.467	42.333	11.15	34.000	45.150	9.550	37.700	47.250	8.817	40.217	49.033	7.533	42.467	50.000	6.367	43.883	50.250
5 min	12.750	29.350	42.100	10.88	33.733	44.617	9.133	37.283	46.417	8.467	39.867	48.333	7.200	42.133	49.333	6.050	43.567	49.617
10 min	12.567	29.167	41.733	10.75	33.600	44.350	9.183	37.333	46.517	8.517	39.917	48.433	7.217	42.150	49.367	6.083	43.600	49.683
15 min	12.850	29.450	42.300	11.00	33.850	44.850	9.567	37.717	47.283	9.100	40.500	49.600	7.633	42.567	50.200	6.633	44.150	50.783
20 min	13.067	29.667	42.733	11.40	34.250	45.650	9.983	38.133	48.117	9.533	40.933	50.467	8.183	43.117	51.300	7.267	44.783	52.050
25 min	13.383	29.983	43.367	11.77	34.617	46.383	10.48	38.633	49.117	9.950	41.350	51.300	8.567	43.500	52.067	8.050	45.567	53.617
30 min	13.533	30.133	43.667	11.87	34.717	46.583	10.63	38.783	49.417	10.15	41.550	51.700	8.833	43.767	52.600	8.300	45.817	54.117
			255.900			272.43			286.87			299.83			304.87			309.87
	FL	30 epochs																
0 min	3.450	0.233	3.683	2.583	0.283	2.867	2.183	0.250	2.433	1.833	0.250	2.083	1.567	0.317	1.883	1.483	0.150	1.633
5 min	5.583	2.600	8.183	4.433	2.633	7.067	3.867	2.633	6.500	3.350	2.517	5.867	2.950	2.600	5.550	2.783	2.350	5.133
10 min	7.217	3.517	10.733	5.833	3.700	9.533	5.233	3.833	9.067	4.683	3.950	8.633	4.350	3.950	8.300	4.217	3.733	7.950
15 min	9.533	4.150	13.683	8.250	4.350	12.600	7.233	4.667	11.900	6.633	4.667	11.300	6.050	5.017	11.067	5.800	4.933	10.733
20 min	10.700	4.900	15.600	9.300	5.233	14.533	8.567	5.600	14.167	7.983	5.867	13.850	7.550	6.117	13.667	7.233	6.217	13.450
25 min	11.600	5.183	16.783	10.10	5.517	15.617	9.367	6.050	15.417	8.633	6.317	14.950	8.500	6.517	15.017	8.217	6.817	15.033
30 min	12.967	5.817	18.783	11.57	6.217	17.783	10.78	6.767	17.550	9.967	7.000	16.967	9.567	7.267	16.833	9.350	7.467	16.817
			83.767			77.133			74.600			71.567			70.433			69.117

HL - PM - RESULTS

gap	0 min			1 min			2 min			3 min			4 min			5 min		
horizon																		
	Naive																	
0 min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5 min	5.667	5.667	11.333	5.767	5.767	11.533	5.817	5.817	11.633	6.167	6.167	12.333	6.267	6.267	12.533	5.800	5.800	11.600
10 min	5.817	5.817	11.633	5.983	5.983	11.967	6.217	6.217	12.433	6.767	6.767	13.533	7.283	7.283	14.567	7.683	7.683	15.367
15 min	5.783	5.783	11.567	5.917	5.917	11.833	6.117	6.117	12.233	6.750	6.750	13.500	7.467	7.467	14.933	7.950	7.950	15.900
20 min	6.467	6.467	12.933	6.567	6.567	13.133	6.700	6.700	13.400	7.117	7.117	14.233	7.750	7.750	15.500	7.900	7.900	15.800
25 min	6.233	6.233	12.467	6.350	6.350	12.700	6.550	6.550	13.100	7.050	7.050	14.100	7.817	7.817	15.633	8.033	8.033	16.067
30 min	6.733	6.733	13.467	6.817	6.817	13.633	7.083	7.083	14.167	7.750	7.750	15.500	8.683	8.683	17.367	9.167	9.167	18.333
			73.400			74.800			76.967			83.200			90.533			93.067
	MLR																	
0 min	5.250	46.733	51.983	5.367	46.717	52.083	5.767	46.550	52.317	6.567	46.150	52.717	7.833	45.550	53.383	9.167	45.050	54.217
5 min	3.550	42.050	45.600	3.133	46.533	49.667	2.867	49.267	52.133	2.600	51.900	54.500	2.917	52.417	55.333	3.183	52.933	56.117
10 min	0.017	91.367	91.383	0.000	91.250	91.250	0.000	90.683	90.683	0.000	89.483	89.483	0.000	87.617	87.617	0.000	85.783	85.783
15 min	5.750	22.017	27.767	5.900	22.183	28.083	6.250	21.967	28.217	7.150	21.667	28.817	8.550	21.200	29.750	9.550	20.367	29.917
20 min	3.117	44.167	47.283	3.150	44.383	47.533	3.383	44.083	47.467	3.933	43.433	47.367	4.867	42.500	47.367	5.700	41.500	47.200
25 min	4.050	42.350	46.400	3.700	46.583	50.283	3.583	50.633	54.217	4.017	53.417	57.433	4.767	54.567	59.333	5.217	55.267	60.483
30 min	2.267	72.433	74.700	1.933	76.683	78.617	1.633	79.617	81.250	1.683	80.917	82.600	1.333	81.100	82.433	1.283	81.217	82.500
			333.133			345.43			353.97			360.20			361.83			362.00
	ARMA																	
0 min	3.583	2.317	5.900	3.383	2.683	6.067	2.717	1.850	4.567	2.167	1.600	3.767	1.950	1.383	3.333	1.533	1.217	2.750
5 min	7.533	0.367	7.900	7.733	0.350	8.083	8.167	0.250	8.417	9.317	0.200	9.517	11.133	0.217	11.350	12.97	0.217	13.183
10 min	7.900	0.433	8.333	8.100	0.433	8.533	8.550	0.350	8.900	9.583	0.283	9.867	11.450	0.283	11.733	13.28	0.283	13.567
15 min	8.150	0.300	8.450	8.367	0.317	8.683	8.883	0.267	9.150	9.967	0.250	10.217	11.833	0.250	12.083	13.67	0.333	14.000
20 min	8.367	0.267	8.633	8.500	0.333	8.833	9.017	0.283	9.300	10.17	0.283	10.450	12.033	0.283	12.317	13.80	0.300	14.100
25 min	8.400	0.183	8.583	8.583	0.183	8.767	9.083	0.250	9.333	10.27	0.233	10.500	12.133	0.233	12.367	13.97	0.233	14.200
30 min	8.467	0.050	8.517	8.700	0.050	8.750	9.267	0.083	9.350	10.47	0.083	10.550	12.333	0.083	12.417	14.17	0.083	14.250
			50.417			51.650			54.450			61.100			72.267			83.300
	MLF	6 - 15 epochs																
0 min	1.833	1.450	3.283	1.700	1.583	3.283	1.683	2.067	3.750	2.317	2.350	4.667	2.483	2.583	5.067	2.300	3.317	5.617
5 min	7.517	0.567	8.083	7.583	0.550	8.133	7.967	0.533	8.500	9.117	0.483	9.600	10.917	0.417	11.333	12.55	0.467	13.017
10 min	7.633	0.683	8.317	8.333	0.233	8.567	8.867	0.200	9.067	9.967	0.200	10.167	11.817	0.183	12.000	13.57	0.183	13.750
15 min	7.783	0.833	8.617	8.383	0.517	8.900	8.883	0.583	9.467	9.967	0.517	10.483	11.833	0.517	12.350	13.67	0.517	14.183
20 min	7.833	0.883	8.717	8.600	0.300	8.900	9.050	0.317	9.367	10.23	0.300	10.533	12.083	0.283	12.367	13.87	0.233	14.100
25 min	7.933	0.983	8.917	8.650	0.233	8.883	9.200	0.217	9.417	10.37	0.233	10.600	12.233	0.233	12.467	14.00	0.333	14.333
30 min	8.133	1.183	9.317	8.717	0.083	8.800	9.283	0.083	9.367	10.47	0.067	10.533	12.333	0.067	12.400	14.15	0.050	14.200
			51.967			52.183			55.183			61.917			72.917			83.583
	RBF	8 - 200 epochs																
0 min	1.583	1.367	2.950	1.483	1.550	3.033	1.200	1.833	3.033	1.433	2.467	3.900	1.750	2.783	4.533	1.317	4.017	5.333
5 min	8.517	0.000	8.517	8.750	0.000	8.750	9.317	0.000	9.317	10.52	0.000	10.517	12.383	0.000	12.383	14.22	0.000	14.217
10 min	8.517	0.000	8.517	8.750	0.000	8.750	9.317	0.000	9.317	10.52	0.000	10.517	12.383	0.000	12.383	14.22	0.000	14.217
15 min	8.517	0.000	8.517	8.750	0.000	8.750	9.317	0.000	9.317	10.52	0.000	10.517	12.383	0.000	12.383	14.22	0.000	14.217
20 min	8.517	0.000	8.517	8.750	0.000	8.750	9.317	0.000	9.317	10.52	0.000	10.517	12.383	0.000	12.383	14.22	0.000	14.217
25 min	8.517	0.000	8.517	8.750	0.250	9.000	9.317	0.250	9.567	10.52	0.250	10.767	12.383	0.450	12.833	14.20	0.517	14.717
30 min	8.517	0.000	8.517	8.750	0.000	8.750	9.317	0.000	9.317	10.52	0.000	10.517	12.383	0.000	12.383	14.22	0.000	14.217
			51.100			52.750			56.150			63.350			74.750			85.800

	ELM	10 - 100 epochs																
0 min	2.650	0.917	3.567	2.633	1.067	3.700	2.633	1.167	3.800	3.050	1.483	4.533	3.567	1.733	5.300	4.050	2.300	6.350
5 min	7.667	0.650	8.317	7.750	0.633	8.383	8.117	0.600	8.717	9.133	0.567	9.700	10.900	0.600	11.500	12.55	0.500	13.050
10 min	7.833	0.817	8.650	8.183	0.317	8.500	8.533	0.267	8.800	9.667	0.250	9.917	11.533	0.250	11.783	13.37	0.250	13.617
15 min	7.883	0.867	8.750	8.483	0.250	8.733	8.883	0.183	9.067	10.03	0.183	10.217	11.867	0.217	12.083	13.70	0.217	13.917
20 min	7.933	0.917	8.850	8.450	0.417	8.867	8.883	0.383	9.267	10.02	0.367	10.383	11.883	0.433	12.317	13.65	0.450	14.100
25 min	8.000	0.983	8.983	8.700	0.100	8.800	9.250	0.117	9.367	10.43	0.100	10.533	12.300	0.100	12.400	14.08	0.133	14.217
30 min	8.167	1.150	9.317	8.750	0.150	8.900	9.300	0.133	9.433	10.48	0.117	10.600	12.317	0.083	12.400	14.07	0.083	14.150
			52.867			52.183			54.650			61.350			72.483			83.050
	SOM																	
0 min	5.367	18.917	24.283	4.883	22.017	26.900	3.950	27.017	30.967	3.817	30.933	34.750	4.217	34.400	38.617	4.317	36.833	41.150
5 min	5.467	19.017	24.483	4.983	22.117	27.100	4.167	27.233	31.400	4.183	31.300	35.483	4.667	34.850	39.517	4.467	36.983	41.450
10 min	5.533	19.083	24.617	5.150	22.283	27.433	4.767	27.833	32.600	4.667	31.783	36.450	4.950	35.133	40.083	4.767	37.283	42.050
15 min	5.500	19.050	24.550	5.067	22.200	27.267	4.417	27.483	31.900	4.400	31.517	35.917	4.983	35.167	40.150	5.033	37.550	42.583
20 min	5.567	19.117	24.683	5.250	22.383	27.633	4.533	27.600	32.133	4.417	31.533	35.950	5.050	35.233	40.283	5.283	37.800	43.083
25 min	5.750	19.300	25.050	5.383	22.517	27.900	4.683	27.750	32.433	4.400	31.517	35.917	5.083	35.267	40.350	5.533	38.050	43.583
30 min	5.967	19.517	25.483	5.517	22.650	28.167	4.917	27.983	32.900	4.817	31.933	36.750	5.600	35.783	41.383	5.817	38.333	44.150
			148.867			165.50			193.37			216.47			241.77			256.90
	FL	40 epochs																
0 min	1.317	0.717	2.033	1.183	0.767	1.950	1.133	0.833	1.967	1.367	1.067	2.433	1.633	1.267	2.900	1.583	1.883	3.467
5 min	7.667	0.533	8.200	7.833	0.500	8.333	8.300	0.433	8.733	9.317	0.400	9.717	11.033	0.317	11.350	12.85	0.300	13.150
10 min	7.917	0.500	8.417	8.117	0.517	8.633	8.517	0.467	8.983	9.533	0.417	9.950	11.333	0.400	11.733	13.12	0.433	13.550
15 min	8.050	0.417	8.467	8.250	0.433	8.683	8.767	0.433	9.200	9.833	0.367	10.200	11.700	0.367	12.067	13.42	0.333	13.750
20 min	8.267	0.467	8.733	8.467	0.483	8.950	8.917	0.400	9.317	10.03	0.417	10.450	11.900	0.417	12.317	13.65	0.417	14.067
25 min	8.250	0.483	8.733	8.483	0.500	8.983	8.983	0.467	9.450	10.08	0.417	10.500	11.933	0.467	12.400	13.65	0.517	14.167
30 min	8.417	0.433	8.850	8.617	0.483	9.100	9.183	0.517	9.700	10.32	0.500	10.817	12.150	0.467	12.617	13.98	0.467	14.450
			51.400			52.683			55.383			61.633			72.483			83.133

S

Synopsis

Introduction
The main aim of Dynamic Traffic Management is efficient and effective use of the existing traffic infrastructure network. To reach this goal, traffic operators take measures, based on the current traffic situation, control schemes and information services at hand, that (try to) influence and distribute traffic in such a manner that it makes optimal use of the present road infrastructure.

As mentioned, traffic measures are nowadays taken based on the *current* traffic situation. If information of the (near) *future* traffic situation would be available, the efficiency of the infrastructure network could be further improved. Hence, there is need for tools that are able to predict the near-future traffic state. Furthermore, traffic throughput is at its maximum just before the traffic flow breaks down into congestion after which a time consuming, hysteresis based traffic stream regeneration sets in. This hysteresis based regeneration is a process that is poorly grasped by conventional traffic models, stationary as well as dynamic ones. Combining these issues leads to the demand for a novel prediction tool: a reliable and accurate congestion prediction tool.

This study
In this dissertation, the performances of models that were developed to produce accurate congestion prediction are compared. The prediction horizon is short-term period of 5, 10, 15, 20, 25, or 30 minutes. All assessed models are based on data driven methods. The methods that were used to build the models are:

- *The naïve method*: a 'do-nothing-scenario' method. This method assumes that during the prediction horizon the congestion state of the traffic system is stationary at the location of interest;

- *Multi Linear Regression (MLR)*: the model's output ('congestion' or 'no congestion') within the short-term prediction horizon is linear depending on the explanatory input variables;

- *Auto Regression Moving Average (ARMA) Time Series Analysis*: the models are calibrated on a sequence of data points measured at successive times, spaced at uniform time intervals. They depend linearly on previous data points and are able to capture historical patterns. The models use previously witnessed patterns in time to predict future outcomes;

- *Multi Layer Feed-forward (MLF) Artificial Neural Networks (ANNs)*: Artificial Neural Network models are non-linear statistical data models that are used to model complex relationships between input variables and (desired) output variables. The architecture of MLF ANNs usually exists of three layers: the input layer, the hidden layer and the output layer. Each layer holds elementary processing units called neurons that pass on incoming signals after they are transformed by a non-linear sigmoid function. During the training fase (calibration), MLF ANNs are offered desired or target outputs. The difference between the actual model output and the target output is used adjust the model's parameters. The algorithm that describes this process is called the back-propagation learning rule;

- *Radial Basic Function (RBF) Artificial Neural Networks (ANNs)*: RBF ANNs seem very similar to MLF ANNs, however, the difference being that the transformation function is not sigmoid but Gaussian;

- *Elman (State-Space) Artificial Neural Networks (ANNs)*: *)*: Elman ANNs seem very similar to MLF ANNs, however, the difference being that they are partial recurrent ANNs where information coming from neurons of the hidden layer serve as additional input in the next time step, the so-called context. This results in ANNs that are capable of storing historic data in the context layer;

- *Self Organising Map (SOM) Artificial Neural Networks (ANNs)*: All ANNs mentioned before are supervised ANNs, meaning that during the calibration fase the ANNs are offered desired or target outputs. SOM ANNs are unsupervised and try to cluster input data according to to statistical regularities present in the input data;

- *Fuzzy Logic (FL)*: FL is based on the analogy of the reasoning of people; they do not require precise, numerical information input, and yet they are capable of highly adaptive control by transforming vague input through the use of membership functions into crisp outcomes.

The data sets that were used to develop the models were acquired through dual induction loops during the month May of 2001 in the Netherlands at the clover leaf junction locations 'Beekbergen' and 'Hoevelaken'. Data were acquired in one-minute time bins that consist of information on mean vehicle speed, standard deviation of vehicle speed, and intenisities per vehicle length class. Vehicles length classes (three of them) are divided into vehicles with a length of up to 5.10 meters, vehicles with a length between 5.10 and 12.50 meters, and vehicles with a length of over 12.50 meters. Furthermore, an occupancy percentage is given and a congestion indicator that flags whether the AID signal has been shown on portal signs to drivers. Data were gathered around the clock and after examination filtered to obtain data that was acquired during the morning (06.00 – 10.59) and evening peak (15.00 – 19.59) period.

The data sets were split in four subsets, each containing one work week of data. Models were then development based on each method and for each prediction horizon. The developed models were calibrated and cross-validated. The measurements of effectiveness (MOE's) are performed by establishing the Mean Absolute Percentages Error (MAPE) of each model. The models were also assessed under the use of a congestion gap filling procedure to mimic higher aggregation levels. Additionally, sensitivity analysis was performed on the MLR models and the MLF ANN models.

Results and conclusions
SOM models, FL models and ARMA models are equally as good as or outperformed by the naïve models, meaning that these models do not have added value under the data acquisition circumstances and should therefore not be considered as a congestion prediction tool.

The supervised ANN models show the best results and when their mutual scores are compared there is little difference. These methods are clearly the best choice as it comes to congestion prediction.

Remarkable are the findings that MLR models have occupancy and intensities of the shortest vehicle class as their most significant variables, while the supervised ANNs' most important variables are mean speed of all, but at least of the shortest, vehicle classes. Apparently, non-linear methods predominately use the information that is stored in mean speed data, while linear models are primarely served by information stored in occupancy and intensity.

To get good predictions, one has to have access to data gathered by detectors that are upstream of the bottleneck detector. Also, the bottleneck detector (target detector, i.e. the first detector to report congestion) needs to suffer from congestion for at least more than 10% of the time or should not suffer from stop-and-go congestion. If both criteria are violated the performance of the model will most likely be low.

The findings on the optimum aggregation level by making use of the congestion gap filling procedure are not straightforward. Perhaps the way congestion occurs is of influence (stop-and-go congestion versus longer periods of congestion), maybe the procedure is not valid enough. However, the data that were at our disposal cannot be transformed into other aggregation levels, especially if one considers the standard deviation from the mean speed. If one wants to examine the optimum aggregation level, one needs individual vehicle data to build several distinctive aggregation level data sets, develop models on those data sets, calibrate and cross-validate them and then compare results; this obviously is a topic for further research.

S

Synthese

Inleiding
Het belangrijkste doel van Dynamisch VerkeersManagement is efficiënt en effectief gebruik van het aanwezige infrastructuurnetwerk. Om dit doel te bereiken nemen wegverkeersleiders maatregelen die het verkeer geleiden, zodat dit op een optimale manier over het huidige wegennetwerk kan worden afgewikkeld. De in te zetten maatregelen worden genomen op basis van het huidige verkeersbeeld en eventueel door het activeren van vooropgezette scenario's die in werking treden als bepaalde grenswaarden van verkeersindicatoren overschreden worden.

Echter, het gebruik van het wegennetwerk is suboptimaal, doordat maatregelen *reactief* ingezet worden. Indien wegverkeerleiders de beschikking zouden hebben over het verkeersbeeld in de nabije toekomst, zou de inzet van maatregelen *proactief* kunnen plaatsvinden. Hiermee zou de afwikkeling van het verkeer verder geoptimaliseerd kunnen worden. Om dit te bewerkstellingen is er dus behoefte aan een verkeersvoorspeller. Voorts geldt dat de maximale verkeersdoorstroming wordt bereikt vlak voordat de verkeersstroom omslaat in congestie én dat de opheffing van congestie een tijdrovend proces is als gevolg van het hysterese-effect. Bovendien zijn conventionele verkeersmodellen, zowel statische als dynamische, slecht in staat om dit hystere-effect te modelleren. Dit alles resulteert in de vraag naar een nieuw, betrouwbaar en accuraat congestievoorspellingsmodel.

Dit onderzoek
In dit proefschrift worden de prestaties van modellen die ontwikkeld zijn om tot accurate congestievoorspellingen te komen vergeleken. De modellen zijn ontwikkeld voor verschillende voorspellingsperioden, namelijk voor 5, 10, 15, 20, 25 en 30 minuten. Alle ontwikkelde modellen zijn gebasseerd op zogenaamde data-gedreven methoden. De methoden die als basis voor de modellen dienen zijn:

- *De naïve methode*: een 'doe-niets-scenario' methode. Deze methode gaat er van uit dat de congestietoestand van het verkeersbeeld gedurende de voorspellingsperiode ongewijzigd blijft;

- *Multi Lineaire Regressie (MLR)*: gedurende de voorspellingsperiode geldt dat de uitvoer van het model ('congestie' of 'geen congestie') lineair afhankelijk is van de verklarende invoervariabelen;

- *Auto Regression Moving Average (ARMA) Tijdreeksen Analyse*: de modellen worden gecalibreerd op een volgorde van datapunten die achtereenvolgens op vaste tijdsintervallen gemeten zijn. Ze zijn lineair afhankelijk van vorige datapunten en kunnen hierdoor historische patronen vastleggen. De modellen gebruiken deze historische patronen om toekomstige uitkomsten te voorspellen;

- *Multi Layer Feed-forward (MLF) Artificiële Neurale Netwerken (ANNs)*: Artificiële Neurale Netwerk modellen zijn non-lineair statistische data modellen die gebruikt worden om complexe relaties tussen invoervariabelen en uitvoervariabelen te modelleren. De netwerkarchitectuur van MLF ANNs bestaat meestal uit drie lagen: een invoerlaag, een verborgen laag en een uitvoerlaag. Iedere laag bestaat uit bouwstenen die neuronen genoemd worden en die binnenkomende signalen na bewerking door een non-lineaire sigmoïde transformatiefunctie doorgeven. Gedurende het leerproces (calibratiefase) krijgen MLF ANN modellen invoerdata aangeboden met bijbehorende gewenste uitvoerdata (doeldata). Het verschil tussen het door het MLF ANN model gegenereerde uitkomst met de gewenste uitkomst wordt gebruikt om de modelparameters bij te stellen. Het algoritme dat dit proces beschrijft staat bekend als de back-propagation leerregel;

- *Radial Basic Function (RBF) Artificiële Neurale Netwerken (ANNs)*: RBF ANNs lijken erg veel op MLF ANNs. Het verschil bevindt zich in de transformatiefunctie die niet sigmoïde is, maar Gaussisch;

- *Elman (Temporele-Spatiële) Artificiële Neurale Netwerken (ANNs)*: Elman ANNs lijken eveneens veel op MLF ANNs. Ze verschillen doordat ze gedeeltelijke recurrente ANNs zijn, waarbij informatie die afkomstig is uit de verborgen laag als additionele invoer in de volgende tijdstap wordt ingebracht (de zogenoemde context). Dit resulteert in ANNs die historische informatie in de contextlaag kunnen vasthouden;

- *Self Organising Map (SOM) Artificiële Neurale Netwerken (ANNs)*: Alle hierboven genoemde ANNs zijn modellen die onder supervisie staan, doordat gedurende de calibratie gewenste uitkomsten aan invoerdata gekoppeld worden. SOM ANNs staan niet onder supervisie en proberen gedurende de calibratie statistische regelmatigheden in invoerdata te clusteren. Indien daarna invoerdata worden aangeboden worden deze tot het meest gelijkende cluster toegedeeld.

- *Fuzzy Logic (FL)*: FL is gebasseerd op de analogie van het redeneren van mensen. De methode gebruikt geen precise numerieke invoer, maar transformeert vage invoer met behulp van waarheidswaarden tussen ‘0’ en ‘1’ (iets kan een beetje waar zijn) naar een uitvoerwaarde die uiteindelijk terug getransformeerd wordt naar een precieze uitkomst.

De databestanden die gebruikt zijn om de modellen te ontwikkelen zijn gedurende de maand mei van 2001 op de knooppunten Beekbergen en Hoevelaken ingewonnen met behulp van lusdetectoren. Data worden per detectielus (per rijstrook) gedurende één minuut ingewonnen en geaggregeerd en bevatten informatie over de gemiddelde snelheid, de standaard deviatie van de gemiddelde snelheid en de intensiteit. Deze drie grootheden worden voor ieder van drie voertuigcategorieen gegeven: voor voertuigen tot 5.10 meter, voor voertuigen tussen 5.10 en 12.50 meter en voor voertuigen die langer dan 12.50 meter zijn. Daarnaast wordt de bezettingsgraad van de detector gedurende de inwinminuut gegeven en de toestand van een congestieindicator die aangeeft of er een AID signaal is afgegeven aan de signaalgevers op het portaal boven de inwinlocatie. De inwinning vond plaats op constante basis en na beoordeling gefilterd op de ochtend (06.00 – 10.59) en avondspits (15.00 – 19.59) perioden.

De databestanden zijn in vieren gedeeld, waarbij elk sub-bestand één werkweek aan data bevat. Deze bestanden zijn vervolgens gebruikt om de modellen te ontwikkelen; voor elke methode en iedere voorspellingsperiode is een model ontwikkeld. Na gecalibratie volgde kruis-validatie. De vaststelling van de modelprestaties is gebeurd op basis van het gemiddelde absolute foutpercentage. Vervolgens zijn de modelprestaties vastgelegd door gebruik te maken van een congestiegat vulprocedure die een hoger aggregatieniveau imiteerd. Ten slotte is een gevoeligheidsanalyse losgelaten op de MLR modellen en de MLF ANN modellen.

Resultaten en conclusies
De SOM modellen, de FL modellen en de ARMA modellen presteren even goed of slechter dan de naïve modellen. Dit betekent dat deze modellen geen toegevoegde waarde hebben onder de condities waarop de datainwinning heeft plaatsgevonden. Deze modellen zijn daarom ongeschikt om tot betrouwbare en accurate congestievoorspellingen te komen.

De ANN modellen die onder supervisie staan vertonen de beste resultaten terwijl de vergelijking van de onderlinge prestaties weinig verschillen laten zien. Deze methoden zijn de beste keus als het gaat om congestievoorspellingsmodellen.

Opvallend zijn de conclusies met betrekking tot de gevoeligheidsanalyse van de MLR modellen. De bezettingsgraad en de intensiteiten van de kortste voertuigen worden als meest significante variabelen aangemerkt. Dit in contrast met de ANNs die onder supervisie staan, waarbij de gemiddelde snelheid van alle, maar vooral van de kortste, voertuigen als meest significant zijn vastgesteld. Hieruit blijkt dat de non-lineaire modellen voornamelijk informatie afkomstig uit de gemiddelde snelheid gebruiken, terwijl de lineaire modellen voornamelijk informatie uit de bezettingsgraad en intensiteit gebruiken.

Om tot goede voorspellingen te komen is het van belang dat men de beschikbaarheid heeft over data afkomstig van detectoren die stroomopwaarts ten opzichte van de doeldetector liggen. Bovendien is het van belang dat de doeldetector voor tenminste 10% van de tijd waarop de analyses betrekking hebben last heeft gehad van congestie én dat de vorm van congestie geen stop-and-go congestie is. Indien niet aan deze voorwaarden wordt voldaan is de kans groot dat het model slecht zal presteren.

De resultaten met betrekking tot het optimale aggregatieniveau, waarbij gebruik is gemaakt van de procedure waarbij congestiegaten gevuld werden zijn niet duidelijk. Misschien is de manier waarop congestie zichzelf manifesteerd van invloed (stop-and-go tegenover langere congestieperioden), misschien is de procedure niet valide genoeg. Echter, omdat het aggregatieniveau al vaststond kon dit niet omgezet worden naar een ander aggregatieniveau (dit geldt vooral met betrekking tot de standaard deviatie). Om het optimale aggregatieniveau met betrekking tot congestievoorspellingen vast te stellen is het nodig om gebruik te kunnen maken van individuele voertuigdata. Deze kunnen vervolgens tot elk gewenst aggregatieniveau omgezet worden. Met de aldus verkregen bestanden kunnen, analoog aan de in dit proefschrift beschreven procedures, modellen ontwikkeld, gecalibreerd en kruis-gevalideerd worden, waarna de prestatie vergeleken kunnen worden. Dit is echter een onderwerp voor toekomstig onderzoek.

CV

Curriculum Vitae

Giovanni Huisken was born and raised in De Lutte, a small village in the east of The Netherlands. After finishing secondary school Thijcollege in nearby Oldenzaal he moved to Groningen with the intention to study physics. During the next years he extensively assessed the nightlife in Groningen until he was called to serve her Majesty's Royal Army. After completion of his duty he returned to Groningen and studied Applied Physics and specialised in Biophysics. His Master's research was carried out for the Department of Nuclear Medicine at the University Medical Center Groningen on the automation of pattern recognition of PET scanner acquired studies of the left ventricle through the use of a priori information and artificial neural networks. During the execution of this research he decided that the continuation of his professional career should be in science.

He moved back east were he was affiliated with the Transport Research Centre of the University of Twente and started to pursue a Ph.D. on the subject of artificial neural networks in Dynamic Traffic Management. In 1999 he was invited by prof. dr. Stephen Ritchie and prof. dr. Will Recker to the Institute of Transportation Research, University of California, Irvine. His Ph.D. related work ultimately resulted in over twenty conference articles and attendances, some journal papers and book chapters and the dissertation lying before you.

After he left the University of Twente, Giovanni was appointed project manager at the consulting and engineering firm ARCADIS where he performed mobility related research. Subsequently, he did some freelance work in the same field before he joined the consulting firm MuConsult as a project manager. Here he worked on a broad range of traffic and transport related studies: from strategic policy studies to the public transport chip card (OV-chipkaart) to econometric model development (the dynamic automobile market model DYNAMO).

Currently, Giovanni is employed by the largest European system integrator, Capgemini. As a business development manager and project manager, again mobility related, he mainly works on projects with high societal impact. Additionally, he continues to review articles for:
- Transportation Research Part C: Emerging Technologies;
- IEEE Transactions on Intelligent Transportation Systems;
- IEEE Transactions on Systems, Man and Cybernetics, Part A;
- ASCE Journal of Transportation Engineering;
- Simulation Practice and Theory.

The majority of his upcoming spare time, which he is anxious for to regain after the Ph.D. defence, will predominantly be devoted to his family and friends.

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Stellingen behorende bij het proefschrift

Inter-Urban Short-Term Traffic Congestion Prediction

Giovanni Huisken
1 december 2006

i
Congestievorming is een niet-lineair fenomeen.
(dit proefschrift)

ii
Het toevoegen van verkeersgegevens die tijdens eerdere tijdstappen zijn ingewonnen (feedback informatie) aan de meest recente verkeersgegevens als invoer voor modellen leidt niet tot verbetering van congestievoorspellingen.
(dit proefschrift)

iii
Ter plaatse van een bottleneck ingewonnen verkeersgegevens zijn minder relevant voor het voorspellen van congestie op die locatie dan stroomopwaarts ingewonnen verkeersgegevens.
(dit proefschrift)

iv
Een bekende uitspraak van Scott Adams (auteur van de comic “Dilbert”)
“To err is human … to really screw up you need a computer”
is uitbreidbaar tot:
“Fouten maken is menselijk … om er een puinhoop van te maken is een computer nodig … om in totale chaos te geraken helpt een inadequate back-up procedure”.
(dit promotieproces)

v
Maximale benutting van het verkeerssysteem is onwenselijk.

vi
Het is efficiënter voor de verkeersveiligheid om in plaats van de Algemene Periodieke Keuring voor motorvoertuigen een APK voor bestuurdersgedrag op de weg in te voeren.

vii
De door sommige verkeersveiligheidsdeskundigen bij het bepalen van verkeersveiligheidsrisico’s aangedragen expositiemaat ‘weglengte’ wordt ten onrechte gebruikt als risicocijfer.

viii
In de perceptie van veel automobilisten die regelmatig in het stedelijk netwerk verkeren, is “stoplicht” een betere benaming voor de functionaliteit van een verkeersregelinstallatie dan “verkeerslicht”.

ix
Realisering van verkeersbeleid is gestoeld op de notie van gecumuleerde onzekerheden: de onzekerheden die horen bij lange termijn verkeersprognoses, waarbij vaak ook nog eens interactie-effecten genegeerd worden, worden door de politiek vanuit een eigen invalshoek voorzien van nog meer vrijheidsgraden.

x
Appels en peren kun je best vergelijken, je kunt er alleen geen chocola van maken.