Springer

Journal of Mechanical Science and Technology

Journal of Mechanical Science and Technology 23 (2009) 1374~1382

www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-008-1108-z

Multi-agent based traffic simulation and integrated control of freeway corridors: Part 2 integrated control optimization †

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(Manuscript Received June 29, 2007; Revised April 15, 2008; Accepted November 14, 2008)

Abstract

This research aims to optimize the traffic signal cycle and the green light time per traffic signal cycle at ramps and intersections in arterials to maximize the passing traffic volume and minimize the delaying traffic volume in freeway corridors. For this purpose, we developed the MATDYMO (multi-agent for traffic simulation with vehicle dynamics model) and validated it with comparison to commercial software, TRANSYT-7F, for an interrupted flow model and to URFSIM (urban freeway traffic simulation model) for an uninterrupted flow model. These comparisons showed that MATDYMO is able to estimate the traffic situation with only incoming traffic volume. Using MATDYMO, ramp metering and traffic signal control can be optimized simultaneously. We extracted 80 sampling points from the DOE (Design of Experiment) and derived each response from MATDYMO. Then, a neural network was adopted to approximate the objective function, and simulated annealing was used as an optimization method. There are three cases of the objective function: maximization of the freeway traffic volume, minimization of the delay of ramps and arterials, and the satisfaction of both cases. The optimization results showed that traffic flow in freeway corridors can be maintained to a steady stream by ramp metering and signal control.

Keywords: Vehicle dynamics; Multi-agent; Traffic simulation; Integrated control; Ramp metering; Signal strategy; Freeway corridor; Agent simulation

1. Introduction

Freeway corridors consist of urban freeways and parallel arterials that drivers can use alternatively. Ramp metering in freeways and signal control in arterials are contemporary traffic control methods that are applied to improve the traffic conditions of freeway corridors. However, most of the existing studies have focused on either optimal ramp metering in freeways or progressive signal strategies between arterial intersections. For efficient control of freeway corridors, ramp metering and signal control must be considered at the same time. If both of these factors are not considered, the control strategies for freeway operations may negatively affect arterial traffic. On the other hand, traffic congestion and bottleneck phenomenon of arterials due to the increase of travel demand at peak hours and ineffective signal operation may generate an accessibility problem to freeway ramps. Thus, the urban freeway will not be able to perform the duties as a through-traffic process.

To manage an urban freeway efficiently, the traffic stream must be anticipated. The prediction of traffic flow can be categorized as follows. First, the management strategy of the urban freeway and the possible alternatives of the geometrical frame design must be analyzed and evaluated by a simulation model. Second, the prediction must be applied to the development of operation strategies, which has re-

† This paper was recommended for publication in revised form by Associate Editor Kyongsu Yi

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ceived much attention due to the increase in the establishment of strategies such as ATMS (advanced transportation management system) and ATIS (advanced transportation insurance services). The urban freeway management system is required to build efficient management strategies because it is critical to forecast the accurate traffic condition. There has been a steady increase in the need for application of simulation models to forecast traffic congestion or traveling time when the control strategies, such as the metering of an entry ramp and an active navigation system, are to be set up.

However, it is difficult to forecast accurate traffic stream volume, although the forecasting is critical. The majority of forecasting models contain a variety of unknown factors which affect the simulation. Estimations or assumed values are employed because there are many more unknown factors than the achievable traffic data. Therefore, the majority of simulation models are difficult to introduce for forecasting real-time traffic conditions [1].

The real-time traffic condition, including freeways and arterial freeways, should be regarded not as an independent system but as an integrated system dependent on the operational purpose [2] and individual control strategies. Throughout the world, there has been much investigation on this approach, namely, the integrated control method, for the analysis of the traffic system [3]. Taking account of current and future traffic map plans and the sudden increase in traffic volume between cities or regions, this research presents an integral control method that links freeways (ramp metering) with arterial freeways (signal control).

This research aims to optimize the traffic signal cycle and the green light time per traffic signal cycle at ramps and intersections in arterials in order to maximize the passing traffic volume and minimize the delaying traffic volume in freeway corridors. This paper (Part 2: Integrated Control using Optimization Technique), based on the result of the previous paper (Part 1: Simulation and Control Model), runs the optimization of integrated control in an urban freeway traffic axis. We extract 80 sampling points from DOE (design of experiment) and derive each response from MATDYMO. Then, a neural network is adopted to approximate the objective function, and simulated annealing is used as an optimization method. The objective function is processed as three cases: maximization of freeway traffic volume, delay minimization of ramps and arterials, and the satisfaction of both cases. The optimization results showed that traffic flow in freeway corridors can be maintained as a steady stream by ramp metering and signal control.

2. Development of traffic simulation system

In regard to integrated control including ramp metering and signal cycle control, this research introduces another optimization method that is different from the previous integrated control model. In detail, the design point is extracted by DOE and the responses of traffic volume and delayed vehicle density for each design point are obtained by MATDYMO. Data from MATDYMO are adapted to approximate the objective function and constraints by the theory of neural network [4] and are used to normalize the optimization design. This optimization design is realized by using a simulated annealing algorithm [5] for the approximated formulation. The subject freeway model is shown in Fig. 1. FTT denotes the number of delayed vehicles in the freeway, ATT/ATT' is the number of delayed vehicles in the arterial freeway, RD is the number of freeway fraction j, and RC_j is the total capacity in the ramp fraction j. Besides Q_0, c_1 and A_0 are the traffic volume of each fraction, as shown in Figs. 2 and 3. Traffic volume from each entrance ramp (E_1) is set to the value of 10% of the arrived traffic volume (A_0). Delayed vehicle is defined as one so that the speed can be less than 5 km/hr. Traffic inflow to the urban freeway or arterial freeway is shown in Fig. 4 and the detailed data are given by Table 1.

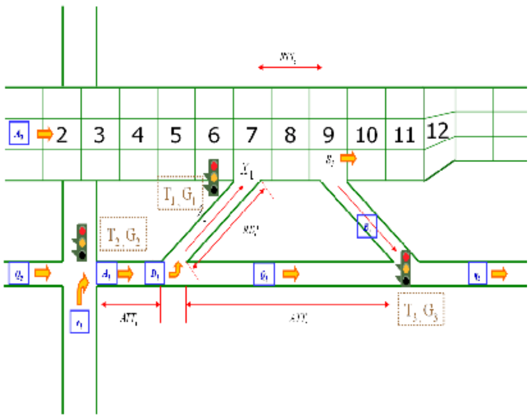

Fig. 1. Test freeway layout.

Table 1. Incoming traffic flow.

Time (min.)	A_0	Q_0	c_1	D_1
1	1000	135	45	180
2	1000	135	45	180
3	1600	105	35	140
4	1600	105	35	140
…	…	…	…	…
60	3200	128	43	171

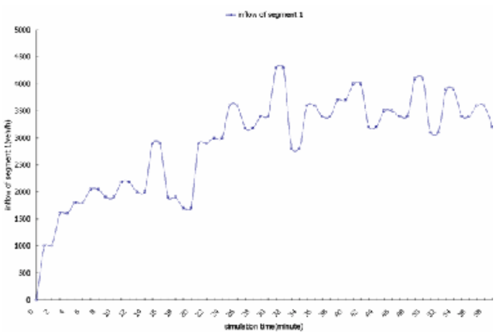

Fig. 2. Incoming traffic flows: inflow of segment 1.

Fig. 3. Incoming traffic flows: on-ramp inflow & off-ramp outflow.

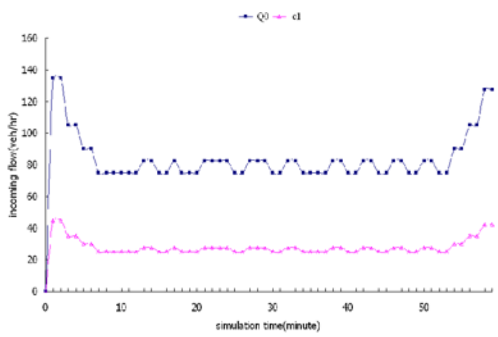

Fig. 4. Incoming traffic flows from arterials.

3. Definition of integrated control optimization

Integrated control is optimized for three cases: the minimization of delay, the maximization of total traffic volume, and the satisfaction of both cases. Then, the results are compared with the simulation results. The entire optimizing design procedure is shown in Fig. 5. The type of the objective function varies according to the object of control. Different objective functions can be used to reach various control objects in a given identical control procedure. The objective function, normally used in the freeway integrated control model, is designed, however, for application to the freeway. Therefore, objective functions in this research are to minimize total number of delayed vehicles during the total driving time, the criterion to measure the freeway efficiency (CASE 1); to maximize the total number of driving vehicles in the urban freeway (CASE 2); and to satisfy both objectives (CASE 3). The objective function for each case is shown below:

1) CASE 1: Minimization of the total number of delayed vehicles

$$Minimize \sum_{i=1}^{M} F = FTT_i + ATT_i + ATT_i^{'} + RD_i \quad (1)$$
$$= f(T_1, T_2, T_3, R_1, R_2, R_3)$$

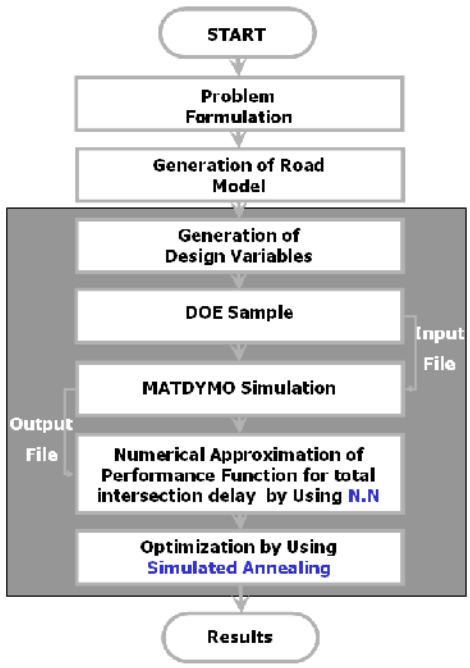

Fig. 5. Flow chart of deterministic optimization.

Table 2. Table of Latin Hypercube arrays.

No.	Design Point of Experiment						Response				
	T1	T2	T3	R1	R2	R3	S1	ATT	ATT'	RD	FTT
1	0.0	122.3	96.5	0.0	13.9	41.5	2085.0	0.0	748.0	0.0	122.3
2	0.2	98.0	137.5	0.1	27.3	69.6	2521.0	10.0	257.0	0.2	98.0
3	0.4	155.7	101.0	0.3	102.5	46.0	2400.0	17.0	201.0	0.4	155.7
4	0.6	91.9	61.5	0.2	79.1	1.6	2269.0	6.0	2.0	0.6	91.9
5	0.8	180.0	149.6	0.3	93.4	142.0	2675.0	15.0	59.0	0.8	180.0
6	0.9	88.9	84.3	0.8	48.4	44.8	2018.0	64.0	12.0	0.9	88.9
7	1.1	139.0	177.0	0.0	10.6	172.5	2407.0	2.0	398.0	1.1	139.0
8	1.3	87.3	170.9	0.9	81.8	41.1	2156.0	2.0	0.0	1.3	87.3
9	1.5	152.7	108.6	0.4	27.1	24.7	2597.0	15.0	189.0	1.5	152.7
10	1.7	131.4	180.0	1.6	104.8	129.9	2210.0	3.0	172.0	1.7	131.4
11	1.9	125.3	148.1	1.4	41.2	121.9	2713.0	31.0	23.0	1.9	125.3
12	2.1	69.1	78.2	0.1	17.5	69.3	2486.0	5.0	308.0	2.1	69.1
13	2.3	99.5	131.4	2.2	97.0	119.7	2106.0	4.0	0.0	2.3	99.5
14	2.5	178.5	93.4	1.5	126.5	53.2	2490.0	11.0	16.0	2.5	178.5
15	2.7	94.9	125.3	0.0	39.7	80.9	2085.0	0.0	739.0	2.7	94.9
...											
80	15.0	113.2	111.7	9.1	7.2	46.6	2560.0	9.0	209.0	15.0	113.2

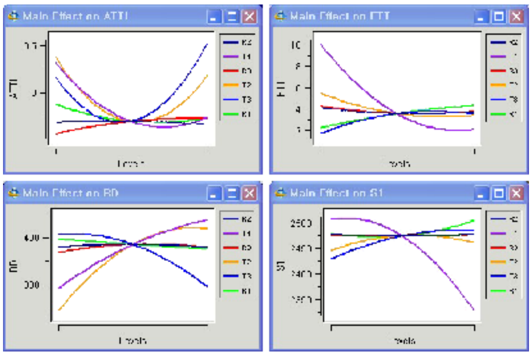

Fig. 6. Main effects of the design variables for response.

2) CASE 2: Maximization of the total number of driving vehicles

$$Maximize \sum_{i=1}^{M} G = S_i = g(T_1, T_2, T_3, R_1, R_2, R_3) \qquad (2)$$

3) CASE 3: CASE 1 + CASE 2

$$Minimize \sum_{i=1}^{M} H = F(CASE1) - \varpi G(CASE2) \qquad (3)$$

The constraints are provided below:

$$\begin{aligned} &Subject\ \ to: \\ &0 \le S_j \le FC_j\,,\ \ 0 \le RD_j \le RC_j \qquad (4) \\ &0 \le T_1 < 15\,,\ \ 0 \le R_1 \le T_1 \\ &60 \le T_2 < 180\,,\ \ 0 \le R_2 \le T_2 \\ &60 \le T_3 < 180\,,\ \ 0 \le R_3 \le T_3 \end{aligned}$$

where, FTT means the number of delayed vehicles in the freeway, ATT / ATT' is the number of delayed vehicles in the arterial freeway, RD is the number of delayed vehicles at the ramp, S_j is the traffic volume in freeway fraction j, FC_j is the total capacity in freeway fraction j, RC_j is the total capacity in ramp j, and ω is the weight function.

3.1 Design of experiment

Among several designs, this research accepts the Latin hypercube method [6], which is available for detecting the main effect and the alteration effect in lower order. The Latin method has remarkable advantages: it can investigate more points and more matrices of each segment or part, can obtain the main effect from fewer experiments, and can extract design points efficiently on a large design scale. Using the extracted design points, as shown in Table 2, this research increases the confidence of the approximation function with 80 design points. Fig. 6 represents the main effect of each variable on the delay in each fraction and on the traffic volume.

3.2 Neural network

An approximate optimization method generates an approximate optimization model that can satisfy the scale of error required by the designer to depict a given system. Normally, a simulation takes more time than optimization because it requires iterative calculations of the objective function and constraints of input design variables through simulation. But by using the approximate optimization method, direct optimization

Table 3. Errors between NN and MATDYMO.

	T1	T2	T3	R1	R2	R3	S1			Σ Delay		
							NN	MAT-DYMO	Error (%)	NN	MAT-DYMO	Error (%)
1	0.31	116.33	172.65	0.84	0.71	0.31	2310.28	2210	4.54	121.09	125	3.13
2	0.61	96.73	91.84	0.71	0.61	0.55	2131.82	2225	4.19	101.43	101	0.42
3	0.92	155.51	128.57	0.08	0.16	0.12	2501.78	2431	2.91	155.09	159	2.46
4	1.22	170.20	77.14	0.49	0.78	0.27	2362.39	2441	3.22	60.27	62	2.79
5	1.53	106.53	121.22	0.96	0.27	0.80	2453.08	2339	4.88	146.44	144	1.70
6	1.84	172.65	131.02	0.80	0.90	0.02	2307.16	2413	4.39	63.64	66	3.57
7	2.14	72.24	126.12	0.98	0.57	0.86	2234.55	2236	0.07	99.89	103	3.02
8	2.45	121.22	138.37	0.69	0.65	0.94	2435.73	2339	4.14	95.02	90	5.58
9	2.76	126.12	108.98	0.10	0.55	0.53	2269.17	2312	1.85	165.68	164	1.02
10	3.06	91.84	111.43	0.22	1.00	0.76	2152.69	2103	2.36	57.88	59	1.89
11	3.37	143.27	99.18	0.39	0.41	0.73	2504.37	2399	4.39	185.31	184	0.71
12	3.67	167.76	135.92	0.16	0.80	0.29	2320.18	2412	3.81	88.29	88	0.33
13	3.98	84.49	153.06	0.92	0.35	0.88	2364.01	2352	0.51	94.91	100	5.09
14	5.20	165.31	170.20	0.51	0.00	0.16	2568.13	2532	1.43	198.43	207	4.14
15	5.51	64.90	94.29	0.59	0.33	0.65	2367.98	2348	0.85	130.68	126	3.71
…	…	…	…	…	…	…	…	…	…	…	…	…
35	14.69	150.61	86.94	0.24	0.02	0.96	2279.95	2286	4.54	219.37	221	0.74

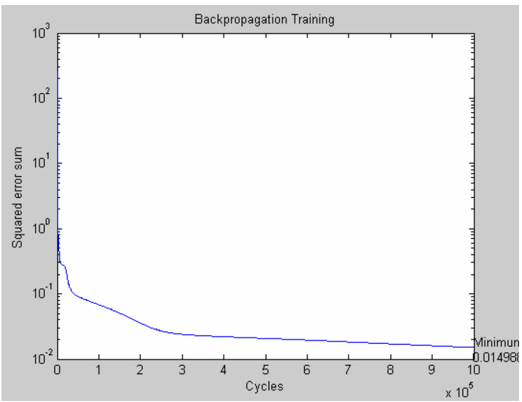

Fig. 7. History of neural network training.

problems such as the calculation of expense and evaluation of practicality of a model can be solved. Neural network [7] is introduced as one of the approximate optimization method and can be used to generate a model to properly depict the relations between the input and output data.

A neural network is built with 6 input nodes, 10 hiding nodes and 4 output nodes. This research trains the neural network for 100,000 iterations using 0.001 error rate and 1.05 learning rate. A built neural network is approximated to the objective function by training it with the back propagation algorithm [8]. Data for training the back propagation algorithm are replaced by the results of MATDYMO according to the input data by DOE. The neural network training result is shown in Fig. 7. The final SSE (sum of squared error) of the trained neural network is 0.014988. The effect of the learning data of the back propagation algorithm on the result is analyzed so that the sensitiveness of the objective function to the learning data of the back propagation algorithm can be analyzed. Error is calculated by inputting 35 voluntary values into MATDYMO and is represented in Table 3. The maximum error was 5.58%. Fig. 8 shows the correlation between each design variable and ATT' in the approximated objective function.

4. Integrated control optimization

Simulated annealing [9] is characterized to be separated from the local minimum and to be converged to the global optimum, permitting design variables that increase the object function probabilistically in the searching procedure. Regarding the annealing procedure of metals, melting metal enters the phase in which its total energy becomes minimum as the temperature decreases

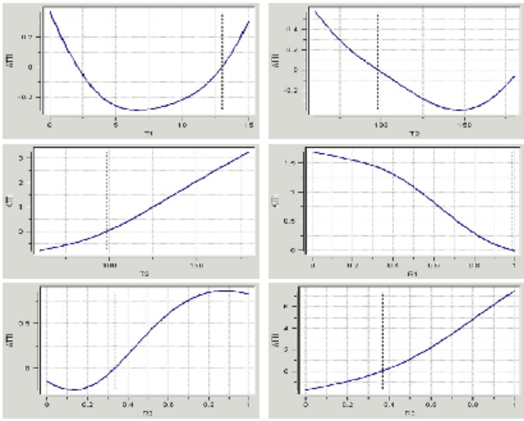

Fig. 8. Interrelation between design variable and ATT.

gradually. When the dissimilarity of energy (ΔE) in phase change from p to q is assumed as Eq. (5) and ΔE is negative, the change in the state is always permitted. But when ΔE is positive, the change is permitted conditionally as much as the probability (P_{accept}) is defined as the Metropolis criterion.

$$\Delta E = E_q - E_p \tag{5}$$

$$P_{accept} = \exp(-\frac{\Delta E}{K_B T}) \tag{6}$$

where, T denotes the temperature and K_B is the Boltzmann constant.

Simulated annealing method can be used to apply the permitted condition changes to a common optimization problem. In this research, the energy is the objective function of either the minimization of delay in each fraction or the maximization of traffic volume in freeway fraction 1. Phase p to the next phase, q, is changed by the following procedure: each signal cycle and the length of the green signal are changed. So, the design variance value, which the objective function does not decrease any further or at which T reaches the target temperature below by increasing the possibility that the objective function is increased by setting the temperature T to the maximum, can be either the minimum delay volume or maximum traffic volume, although the objective function is calculated by the change in each design variable.

Table 4 shows the optimization result for the iteration frequency of 1000 times. Figs. 9, 10, and 11 display the tendency of convergence. ATT is always 0

Table 4. Result of optimization.

Design Variable	Cases of Optimization					
	Maximum Traffic Flow		Minimum Delay		Max.Traffic Flow &Min. Delay	
	initial	final	initial	final	initial	final
T_1	4	11.78	4	13.16	4	9.9
T_2	80	107.34	60	95.15	80	65.11
T_3	160	101.23	70	76.70	160	60.24
R_1	3	11.02	3	11.77	3	9.88
R_2	8	24.66	60	95.15	60	65.10
R_3	40	21.61	70	13.67	70	0.000
Constraint	initial	final	initial	final	initial	final
S_1	2300	2738.78	2100	2390.57	2434	2726.34
ATT	0	0	0	0	8	0
ATT’	8.2	0.001	12	0.088	8.2	0.002
RD	231	50.59	145	0.1	122	22.16
FTT	34	19.628	34	8.18	35	21.18
Σ delay	273.2	70.22	191	8.36	165.2	43.34

Table 5. Errors between optimum and MATDYMO.

Constraint	Optimum	MATDYMO	Error (%)
Minimum Delay			
S_1	2390.565	2279	4.9
Σ delay	8.363553	15	-44.2
Maximum Traffic Flow			
S_1	2738.78	2634	4.0
Σ delay	70.22111	82	-14.4
Max. Traffic Flow & Min. Delay			
S_1	2726.337	2578	5.8
Σ delay	43.34432	43	0.8

for its value so that it is omitted. Table 5 shows the comparison between the optimized value and the real value from MATDYMO.

4.1 CASE 1: Delay minimization

For the delay minimization in each fraction, the objective function is to minimize the sum of FTT, ATT, ATT' and RD, the total number of delayed vehicles in all fractions. As a result, the delay in the beginning period is 191, but the optimized value decreases by 2184.7% to 8.36. Consequently, the passing volume is decreased by 1.4% from 2425 to 2391. After

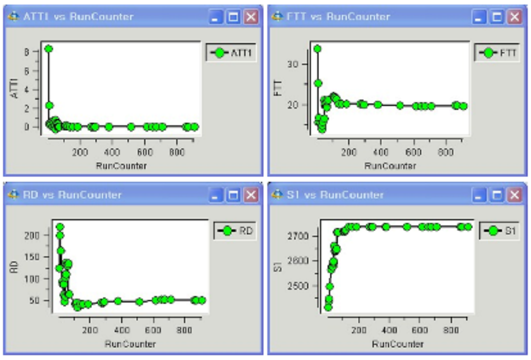

Fig. 9. Acceleration of responses optimization for CASE 1 by SA.

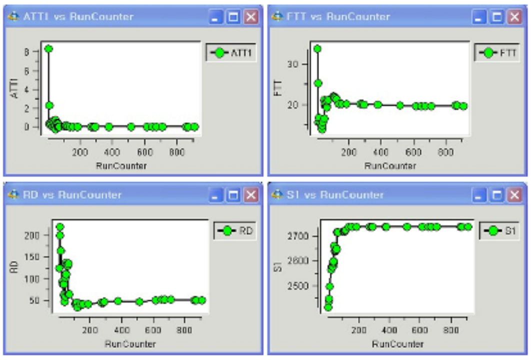

Fig. 10. Acceleration of responses optimization for CASE 2 by SA.

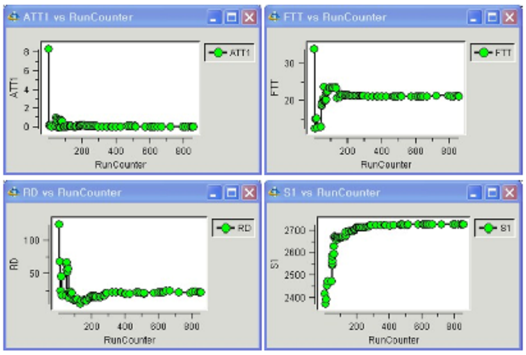

Fig. 11. Acceleration of responses optimization for CASE 3 by SA.

the simulation with establishing the design variables for the above optimized values as the beginning values of MATDYMO, each difference is 4.9% for the optimized design and passing volume and is 44.2% for the total delay. The total delay shows a large error because of the accumulation of the small delay when vehicles attempt to enter a freeway in a real simulation. When each absolute value is compared, error tends to become larger because of the considerably small values of optimization, 8.4 and 15. But the delay appears to be decreased in a real simulation.

4.2 CASE 2: Passing maximization

According to the optimized value for the traffic maximization, the traffic volume appears to increase from 2300 to 2738.8 in freeway fraction 1. Total delay is decreased by 289% from 273.2 to 70.22. Regarding the rate of delay per each fraction to the total delay, the delay in RD, entrance ramp, is dominant and the delay in the main freeway is noticed because of the vehicles going into and out of the ramp. Compared with CASE 1, CASE 2 has more increased delay in main freeway CASE 1 because of the effect of the deceleration at break-in by the large traffic volume in the main freeway. By simulation through MATDYMO with the optimized design variables as the beginning values, the difference between the optimized value and the traffic volume in freeway fraction 1 is 4% for the traffic volume and -14.4% for the total delay.

4.3 CASE 3: Delay minimization+Passing maximization

In CASE 3, with the consideration of both CASES 1 and 2, the optimized value is calculated to satisfy both of the cases. First, the traffic volume in freeway fraction 1 increased by 10.7% from 2434 to 2726, the optimized value. Second, the total delay decreased by 281% from 165.2 to 43.34. Compared with both cases, CASE 3 has a higher total delay than CASE 1 (delay minimization) and lower total delay than CASE 2 (passing maximization). The total traffic volume in freeway fraction 1 of CASE 3 is much larger than that of CASE 1 but similar to or a little smaller than that of CASE 2.

$$\Sigma \text{ Optimum Delay: } case_1 \le case_3 \le case_2 \tag{7}$$

$$\Sigma \text{ Optimum S: } case_1 \le case_3 \le case_2 \tag{8}$$

For the optimized value and the real value, the total delays are 43.3 and 43, respectively, with an error of 0.8%. The traffic volumes in freeway fraction 1 are 2726 and 2578 with 5.8% of error. The result for each case with the real value is given below:

$$\text{Real Delay: } case_1 \le case_3 \le case_2 \tag{9}$$

$$\text{Real S: } case_1 \le case_3 \le case_2 \tag{10}$$

With the results of each case and the comparison of the effectiveness of each variable with, T_1 and R_1 for ramp metering were the most effective variables on the main freeway and T_2 , R_2 for intersection signal control on the arterial freeway. As the traffic volume entering the intersection increases by T_1 and R_1 , the traffic volume entering the freeway gradually increases. Moreover, because of the permission of entering ramp by T_1 and R_1 , the traffic volume in freeway fraction 1 and FTT can be changed. Based on the optimization result, the change of value in RD and FTT was proven to affect the optimization of the total object function. In other words, the traffic stream in the arterial freeway affects that in the main freeway. Therefore, if the integrated control for the traffic axis in an urban freeway is accomplished, the traffic stream in the urban freeway can be controlled. The optimization of CASE 3 is determined as an ideal control method, because it minimizes the number of delayed vehicles in either the ramp or arterial freeway and because it can maximize the total traffic volume when it is applied to real traffic situation control. In addition to these reasons, CASE 3 can maximize the traffic volume in both the urban freeway and arterial freeway by diminishing the possibility of traffic lawbreaking due to the long time spent at a signal.

5. Conclusion

We studied the integrated control of the urban freeway axis by using the predicted result of the urban freeway traffic stream provided by MATDYMO. We optimized ramp metering and traffic signal control through DOE, neural network and simulated annealing for the integrated control of the urban freeway traffic axis with traffic simulation that used vehicle dynamics based on multi agents. We conclude the following:

We developed the traffic simulation system based on MATDYMO using dynamics and also developed agents and situations. Situations were composed of the roads and signals, and the agents consisted of the driver agent and vehicle agent. Also, the results of this study were compared with the results obtained from the traffic forecasting simulation using URFSIM to verify the developed simulation program. Furthermore, the warned situation was investigated with the virtual geometric structure and passing pattern. As a result, URFSIM and this system showed very similar analysis results for the traffic congestion situation. But this system generated more realistic results for easing the traffic congestion situation.

We also sought the definition or the method of optimization for integrated control. The optimization targets were defined as the minimization of the delay by ramp metering, signal cycle control in the arterial freeway, and the maximization and optimization of traffic volume in an urban freeway. The subjects for all three targets were defined, as well. In the result for the optimization, the total passing volume appears to increase from 2434 to 2726 and the total number of delayed vehicles decreases from 165 to 43 for the delay or passing volume optimization. For maintaining a steady stream between urban freeway and arterial freeway, delay or passing volume optimization was determined to be the most appropriate method because it minimized the delay in the arterial freeway and maximized the total passing volume in the urban freeway.

Acknowledgment

This work was supported by grant No. (R01-2004-000-10938-0) from the Basic Research Program of the Korea Science & Engineering Foundation and the fostering project of the Excellent Lab of the Ministry of Education and Human Resources Development (MOE), the Ministry of Commerce, Industry and Energy (MOCIE), and the Ministry of Labor (MOLAB).

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