Fuzzy Model for the Average Delay Time on a Road Ending with a Traffic Light

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Abstract. Urban traffic is continuously increasing and therefore especially in peak-hours an optimized traffic light system can provide significant advantages. As a step towards developing such a system this paper presents a fuzzy model that estimates the average delay times on a road that ends at an intersection with traffic lights. The model was created based on data obtained using a validated microscopic traffic simulator that is based on the Intelligent Driver Model. Simulations were carried out for different traffic flow, traffic signal cycles, and green period values. The newly developed fuzzy model can be used as a module in a traffic light optimization system.

Keywords: Fuzzy model · Average delay time · Traffic light · Microscopic traffic simulator

1 Introduction

The optimization of traffic lights cycles has been intensively investigated in the last decade. The calculation or measurement of delays caused by a road ending in a junction/intersection with traffic lights is one of the key issues in this field. Different models and methods have been used to solve this task so far, and the results may be significantly different from each other depending on whether the intersection is in saturated or near saturated conditions.

Computational intelligence based solutions are widely recognized as suitable tools for control, classification, and other purposes (e.g. [1–6]). Fuzzy controllers and other computational intelligence based methods have been proposed in several works for the optimization of a traffic light at an intersection (e.g. [7–14]). In order to provide a traffic light system with a control solution that determines the optimal traffic signal cycle length and the green period ratio depending on the actual traffic flow values on the intersecting roads, first, one needs to develop a model that describes the behavior of the traffic on a road ending with a traffic light. Hence the goal of the research reported in this paper was to create a fuzzy system that describes the relationship between the average delay time and its parameters, which are traffic signal cycle length, green period ratio, and traffic flow. The data necessary for building the model was obtained using the IDM based microscopic traffic simulator IT MICROSIM [15].

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The rest of this paper is organized as follows. Section 2 describes the parameters and results of the simulation runs, which served as a data source for the model development. Section 3 presents the creation and optimization of our new fuzzy model and the conclusions are drawn in Sect. 4.

2 Simulation Based Investigation of Average Delay Time Values on a Road

The aim of the experiments was to determine the average delay time values depending on the traffic flow, green period ratio, and traffic signal cycle using the microscopic traffic simulator IT MICROSIM [15]. In course of the simulation we considered a 500 m long road ending in an intersection with a traffic light (Fig. 1). The traffic flow was created with randomly arriving vehicles.

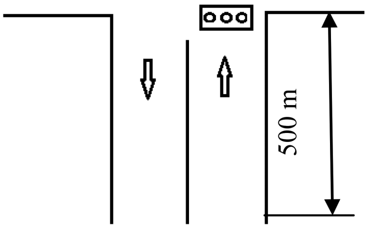

Fig. 1. Road ending in an intersection with a traffic light

The parameters of the simulations were defined as follows. Five values were tried as traffic signal cycle length, i.e. 50, 76, 100, 150, and 200 s, respectively. The traffic signal cycle was composed from two periods with the same durations, the first one was the green period and the second one was the red period. The green period included green light time, 3 s yellow light and 2 s red light, while the red period contained only red light that simulated the time when the cross road gets the green period. Simulations were carried out with a duration of the green period of 25%, 33%, 50%, 67%, and 75% of the total duration of the traffic signal cycle.

In case of the traffic flow eleven distinct values were chosen, i.e. 200, 400, 600, 800, 850, 900, 950, 1000, 1050, 1100, and 1200 vehicle/hour, respectively. Delay times were obtained by subtracting the free-flow travel times from the measured travel times. Free-flow travel times are the travel time values without traffic lights. In the micro-simulator, their value depended on the actual traffic, similar to the real-world situation. Table 1 shows the free-flow travel time values for the traffic flow values used in course of the simulations.

In order to get a detailed picture about the relation between the above-mentioned parameters and the delay times a full factorial experimental design plan was used, i.e. each value of each parameter was tried with each value of the other parameters. It needed $n = 5*5*11 = 275$ simulation runs. For the case of 50% green period ratio the results are shown in Table 2 as well as in Fig. 2.

Table 1. Free-flow travel times

Flow [vehicle/h]	Free-flow travel times [s]	Flow [vehicle/h]	Free-flow travel times [s]
200	34.58	950	37.30
400	35.59	1000	37.41
600	36.19	1050	37.50
800	36.86	1100	37.53
850	37.03	1200	37.58
900	37.17		

Table 2. Average delay times for the 50% green time period ratio [s]

Flow [v/h]	Traffic light cycle length [s]				
	50	76	100	150	200
200	10.63	14.90	17.23	24.42	31.28
400	12.81	17.03	19.60	27.12	35.65
600	16.22	19.62	22.34	31.53	39.41
800	44.45	26.45	27.62	35.58	45.52
850	185.68	31.67	30.27	38.11	46.94
900	218.98	45.83	35.21	42.09	49.38
950	217.97	162.33	56.06	47.76	52.22
1000	221.38	191.40	155.29	62.90	61.67
1050	220.07	191.98	176.02	144.25	95.30
1100	221.18	192.36	177.33	162.73	153.34
1200	222.56	189.96	174.87	162.02	152.21

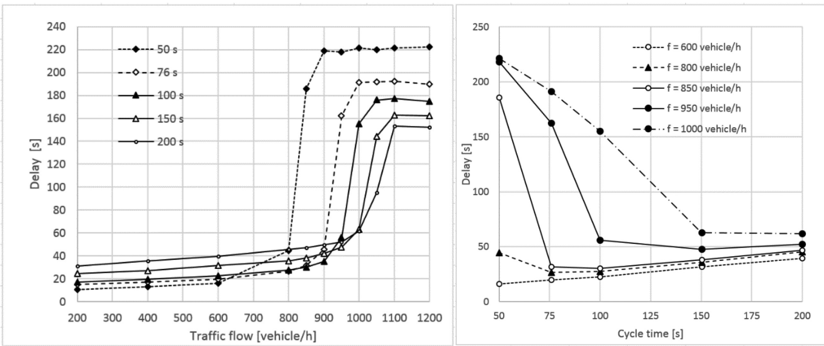

Fig. 2. Average delay times depending on the traffic flow (left) and the traffic light cycle length (right) for the 50% green period ratio

Investigating the results in the left part of Fig. 2 one can recognize that the delay time values can be described by curves that are convex, non-negative, non-decreasing and which depend on the current traffic. For traffic flow values greater than the traffic light cycle capacity, the delay increases until it reaches its maximum value when the road is filled with waiting vehicles. The capacity of a traffic signal cycle is near the value of the abscissa of the inflection point of the graph corresponding to the cycle. One can see that the higher the traffic signal cycle length is, the larger the capacity of the traffic signal cycle becomes.

3 Fuzzy Model for the Average Delay Time

The fuzzy model created is a MISO (Multiple Input Single Output) fuzzy system with three inputs, i.e. green period ratio (GPR), traffic light cycle (TLC), and traffic flow (TF). Its schematic structure is presented in Fig. 3. The range for the three input variables was defined as follows GPR $\in$ [25, 75], TLC $\in$ [50, 200], and TF $\in$ [200, 1200].

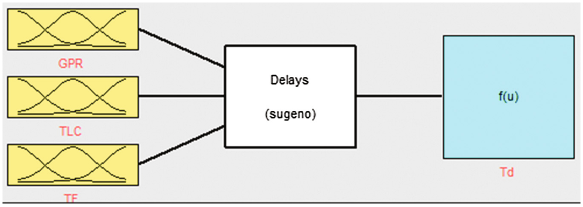

Fig. 3. Fuzzy system

The output of the system is the average delay time (Td). Its range was estimated based on the simulations as $T_d \in [0, 850]$.The system applies Takagi-Sugeno-Kang (TSK) [16] type fuzzy inference and to maintain simplicity triangle shaped membership function type is used for each antecedent fuzzy set. In course of the modeling process several set numbers were tried in each antecedent dimension starting from three up until nine. The best results were obtained with five-five fuzzy sets in the first two input dimensions and eight fuzzy sets in the third one, respectively.

TSK fuzzy inference requires a full coverage of the input space by rule antecedents. Thus, in the actual case the number of necessary rules was $N_R = 5*5*8 = 200$. We opted for a zero order TSK system in order to ensure the fast computation of the output. At the beginning the output of each rule was set to zero. The final parameters of the input fuzzy sets and the consequents of the rules were obtained through a Particle Swarm Optimization (PSO) [17] based tuning process.

At the beginning 275 data tuples formed the whole data set measured during the simulations. From this set 50 data tuples were selected for testing purposes and 225 ones were kept for training the fuzzy system. The tuning aimed the determination of the position of the input sets (support), the relative position of their cores and the output value of the rules. Owing to the fact that the number of parameters to be modified was quite high $N_p = 2*(5 + 5+8) + 200 = 236$, we did not try to find the optimal value for each parameter at the same time, but we modified only one parameter at a time and we repeated the process several times. The algorithm of this iterative tuning is detailed below.

```
For each iteration cycle
  For each input dimension
    For each set of the current dimension
      Find with PSO the optimal position of the support
  For each input dimension
    For each set of the current dimension
      Find with PSO the optimal position of the core
  For each rule
    Find with PSO the optimal consequent value
```

The parameters of PSO were defined as follows. The number of particles in the swarm was 40. The self-confidence coefficient was 2.05, the social coefficient was 2.05 and $c_3 = 0.729$. The number of allowed generations was 10. The number of iteration cycles was 100. The performance of the system was measured by the root mean square of the error expressed in percentage of the output range (RMSEP). At the end of the tuning this value was 0.5706% in case of the training data and 0.5248% in case of the test data, respectively. The resulting input partitions are presented in Figs. 4 and 5.

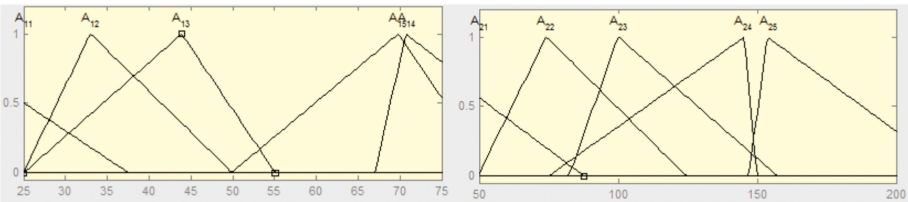

Fig. 4. Input partitions for GPR (left) and TLC (right)

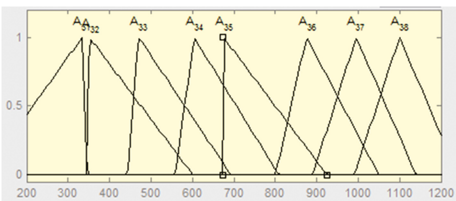

Fig. 5. TF

Figure 6 shows the average delay values measured through simulations (circles) and the T_d values calculated by the fuzzy system in case of the training data set and the test data set, respectively.

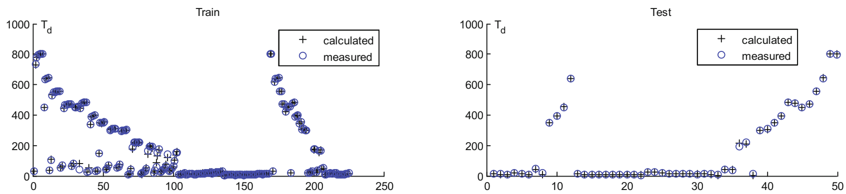

Fig. 6. Average delay time for training (left) and test (right) data sets

4 Conclusions

IT MICROSIM ensures a proper architecture to determine the optimal cycle time values and green period ratios for any traffic flow value by using an arbitrary search technique or design of experiments (DOE) methodology in case of a static traffic flow. However, the application of IT MICROSIM in a real-time system with continuously varying traffic flows is not feasible owing to the high time demand of the simulations. As a first step towards developing a traffic light optimization system that would automatically adjust the green period ratios and traffic light cycle conform to the actual traffic flow in order to achieve an optimal total delay one needs a tool that can calculate the average delay time fast depending on its parameters. This model combined with an efficient computational intelligence based search method (e.g. [18–20]) can be used later to determine the optimal settings for green period ratios and traffic signal cycle.

In this paper, a fuzzy model was presented that applies Takagi-Sugeno-Kang inference and provides a good approximation of the average delay time. The model was created based on data obtained using a validated microscopic traffic simulator that is based on the Intelligent Driver Model. Simulations were carried out for different traffic flow, traffic signal cycle, and green period values. The newly developed fuzzy model can be used as a module in a traffic light optimization system independently from the actual type of the intersection.

Further research will consider the application of a fuzzy rule interpolation based interpolation technique (e.g. [21–23]) in order to reduce the complexity of the rule base, which at its turn determines the time demand of the calculation as well as the time necessary for parameter optimization.

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