TRAFFIC SIGNAL OPTIMIZATION PROGRAM FOR OVERSATURATED CONDITIONS: A GENETIC ALGORITHM APPROACH

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INTRODUCTION

Traffic congestion during peak periods is prevalent for most urban areas. A recent study notes urban arterial systems have experienced increasing traffic congestion (1). Thus, there is a need for effectively managing traffic signal control systems during congested or oversaturated periods. Oversaturated conditions are defined as the condition when vehicles are prevented from moving freely, either because of the presence of vehicles in the intersection itself or because of queue back-up in any of the exit links of the intersection (2). Even though oversaturated conditions may last for a short period, its post effect may take a long time to clear.

Traffic signal coordination and optimization are desired to be cost-effective means of reducing urban traffic congestion, especially when additional road construction is impossible due to either high construction cost or lack of available land. Therefore, optimal traffic control plans should be developed and implemented that would maximize the operational efficiency of existing facilities. This can be achieved by maximizing the use of green time and preventing formation of queue blocking of output flows.

BACKGROUND

Signal Optimization

Current traffic signal optimization programs can be classified into two categories: delaybased models and bandwidth-based models. TRANSYT, a representative delay-based model, minimizes a linear combination of network-wide delay and stops by optimizing cycle length, green split, and offset. In contrast, bandwidth-based programs maximize the sum of directional bands for progression by choosing optimal phase sequence, offset, and cycle length.

The limitation of existing bandwidth-based programs is that their progression does not correspond to the actual traffic flows on the arterial links (3). This is because heavy cross street turning movements may disrupt a progression bandwidth established for arterial through movements. However, an advantage of a bandwidth-based program is its capability for selecting an optimal signal phase sequence (4). Even though delay-based programs are most effective for developing signal timing plans, the existing programs do not optimize phase sequence used. As a consequence, research has been done in the area of combining the merits of delay-based programs and bandwidth-based

programs (5,6,7). However, none of the computer software can optimize all four traffic control parameters (i.e., cycle length, green split, offset, and phase sequence)

Oversaturated Conditions

simultaneously, even for undersaturated conditions.

Signal optimization for oversaturated conditions has been studied since 1960s. Gazis and Potts considered the problem of signal control during peak hours and derived the optimality conditions using variational calculus for an oversaturated one-way street having no turning movements (8). Even though queue length constraints were not considered, Gazis proposed a graphical method to minimize total delay for two oversaturated closely-spaced intersections (9). Michalopoulos and Stephanopoluos proposed an optimal control policy to minimize delay at a system of oversaturated intersections with queue length constraints (10). Kim and Messer developed a dynamic model as a mixed integer linear programming problem to provide an optimal signal timing plan for diamond interchanges during oversaturated conditions (11).

A couple of macroscopic approaches have been developed to consider oversaturated conditions. Rouphail and Akcelik (12) developed a simple analytical model for predicting the effects of queue interaction on delays and queue length at signalized closely-spaced intersections. Prosser and Dunne (13) presented a procedure which explicitly considers queue blocking effects for determining the capacities of movements at closely-spaced intersections. Later, Messer extended the Prosser-Dunne model to a wider range of operating conditions (14). However, none of these models are currently used in traffic signal optimization programs.

MOTIVATION

During oversaturated conditions, vehicle queuing back from the downstream stopline may reach the upstream intersection. This kind of link blockage or spillback may cause a waste in green time at the upstream intersection and lead to a severe capacity reduction. Until the recent release of TRANSYT-7F version 8.1 in March 1998 (15), none of the available traffic signal optimization programs modeled queue blocking effects.

As mentioned earlier, no single existing technique optimizes all four parameters simultaneously. If one or more of the four parameters are non-optimal, a decrease in system performance will result. Thus, the development of a model that simultaneously optimizes all four parameters is essential for maximizing the use of current resources. The presented genetic algorithm-based program optimizes all four parameters simultaneously as well as it models queue blocking effects adequately.

DEVELOPMENT OF GA-BASED PROGRAM

Design Concept

The proposed genetic algorithm-based signal optimization program consists of two main components: a GA optimizer and a mesoscopic traffic simulator. Figure 1 depicts the conceptual framework of the proposed program. The GA optimizer starts by randomly producing a generation of individuals (i.e., traffic signal timing plans). Each individual timing plan is then evaluated through the mesoscopic traffic simulator. The next generation will be evolved by the GA optimizer on the basis of those fitness values obtained from the mesoscopic traffic simulator. The evolution of genetic algorithm is based on a natural selection process. For example, in the case of maximization problem, individuals showing higher fitness values are selected for mating to generate offsprings through genetic algorithm operators. This circulation process of Figure 1 is continued until the maximum number of generations is reached.



FIGURE 1 Conceptual framework for GA-based signal optimization program.

Genetic Algorithm Optimizer

Genetic algorithm

Genetic algorithms are search algorithms based on the mechanics of natural selection and evolution (16). They work with a population of individuals, each representing a possible solution to a given problem. Each individual is assigned a fitness value according to how good a solution to the problem it is. The highly fit individuals are given opportunities to reproduce by cross breeding with other individuals in the population. A new population of possible solutions is thus produced by selecting the best individuals from the current generation and mating them to produce a new set of individuals (17).

Genetic algorithms use three basic operators: reproduction, crossover, and mutation, although further enhanced operators have been suggested and implemented. The reproduction operator selects individuals with higher fitness, while the crossover operator creates the next population from the intermediate population. Finally, the mutation operator is used to explore some areas that have not been searched. More details of genetic algorithm can be found from related literature (16). Schema theorem and building blocks hypothesis are rigorous explanations of how genetic algorithms work. Basically, schema theorem and building block hypothesis say that the number of good components are likely to proliferate as the number of generations evolve (17).

One of the difficulties in applying genetic algorithms is accommodating system constraints. One of the easiest ways to deal with constraints is to run the model, evaluate the objective function, and check to see if any constraints are violated. If constraints are violated, the solution is infeasible and thus has no fitness. The deficiency of this method is that finding a feasible solution set is very difficult and inefficient in a highly constrained problem (22).

Problem formulation

Genetic algorithms maximize fitness value. Thus, to accommodate the minimization problem (delay minimization), the fitness function has to be transformed into a maximization problem. In this case, the original objective function is multiplied by a minus value (e.g., -1) for transformation. The minimization of average delay (AD) formulation and transformed fitness value (FV) are defined as follows:

$$\underset{\{C,g,\theta,p\}}{\text{Minimize:}} \quad AD = \frac{\sum_{i=j}^{Ni} \sum_{j=i}^{Nm} \sum_{j=i}^{Np} q_{ij}^{t}(C, \hat{g}_{ij}, \theta, p)}{\sum_{i=j}^{Ni} \sum_{j=i}^{Nm} \sum_{j=i}^{Np} D_{ij}^{t}(C, \hat{g}_{ij}, \theta, p)}$$
(1)

 \Leftrightarrow Maximize: FV = -AD

Subject to

$$G_{i1} + G_{i2} = G_{i5} + G_{i6} \quad for \ i = 1, \cdots, N_i$$
⁽²⁾

$$G_{i3} + G_{i4} = G_{i7} + G_{i8} \quad for \, i = 1, \cdots, N_i \tag{3}$$

$$\sum_{i=ring} G_{ij} = C \quad for \ i = 1, \cdots, N_i \tag{4}$$

$$G_{ij} \ge MG_{ij} \quad for \ i = 1, \cdots, N_i \quad and \ j = 1, \cdots, N_m \tag{5}$$

$$0 \le \theta_{i,i+1} < C \text{ and } \theta_{i+1,i} = C - \theta_{i,i+1} \quad \text{for } l = 1, \cdots, N_l$$
(6)

$$MinC \le C \le MaxC \tag{7}$$

 $g_{ii}, C, \theta \ge 0$ and Integer

where

С	=	cycle length (sec);
\hat{g}_{ij}	=	effective green time (unimpeded green time) for j at i (sec);
$\boldsymbol{\theta}_{i,i+1}$	=	offset between intersection i and $i+1$ (left to right, sec);
p	=	phase sequence;
i	=	intersection;
j	=	movement (j=1,,12, NEMA phases plus right turns);
t	=	simulation time interval;
N _i	=	total number of intersections;
N _m	=	total number of movements;
N _p	=	time period (sec);
q_{ij}^t	=	queue length at j during time t at i (vehicles);
D_{ij}^t	=	(unimpeded) departed vehicles at j during time t at i (vehicles);
G_{ij}	=	green time (only integer values) for j at i (sec);
MG _{ij}	=	minimum green time for j at i (sec);
MinC	=	minimum cycle length (sec); and
MaxC	'=	maximum cycle length (sec).

The objective function shown in Equation 1 represents the average delay for the entire system. Equations 2 and 3 indicate the barrier constraints; whereas, Equations 4 and 5 are the cycle length and minimum green time constraints. Equation 6 indicates that the offset should be between 0 and cycle length -1; whereas, Equation 7 confines the cycle length to lie between a user-specified minimum and maximum cycle length. The minimum cycle length must be chosen so that all minimum green time constraints are initially feasible. Finally, Equation 8 restricts integer values for green split, cycle length, and offset.

Coding/decoding scheme

The theoretical foundations of genetic algorithms utilize binary strings to represent potential solutions. In this research, a special decoding scheme described below was developed to accommodate the traffic signal optimization constraints.

A fraction-based decoding scheme

A fraction-based decoding scheme, shown in Figure 2, was developed and employed to accommodate the traffic signal control constraints such as the controller's barrier, minimum phase times, and cycle length range. Instead of producing individual traffic signal parameters separately, fractional values are utilized to prorate available green

(8)

times. For an intersection, the genetic algorithm optimizer uses 4-6 fractional values depending on the use of overlap phases. For example, if overlap phases are allowed on both the main and cross streets, 6 fractional values are needed. Fractional value f_1 is used to calculate cycle length; f_2 divides the cycle length into the main street and cross street phase times, and f_3 through f_6 determine the green times of the eight NEMA phases. If the cross street prevents overlap phases, fractional value f_6 is not required since f_5 is equal to f_6 . It is noted that the proposed fraction-based decoding scheme guarantees that the traffic signal control parameters from the genetic algorithm-based optimizer satisfy the constraints of Equations 2-8.



FIGURE 2 A fraction-based decoding scheme for signal phasing.

An example of decoding

An example of a fraction-based decoding scheme for two intersections is presented. Suppose that an individual (i.e., a signal timing plan for two intersections) consists of 14 decision variables: one for cycle length, ten for the green splits of the two intersections, two for phase sequences of the two intersections, and one for offset. As mentioned earlier, each intersection requires five fractional values to determine green splits. A binary vector is used to represent the decision variables.

The following explains how the decision variables are decoded. Consider the following binary vector representing 14 decision variables that are separated by a semicolon and together consist of 70 digits. The first variable (represented by the first 6 digits), corresponds to the cycle length. The 2nd through the 6th variables are used for determining the green splits of intersection number one, while the 7th through the 11th variables are used to determine the green splits of intersection number two. The 12th and

 f_1

the 13th variables are used to determine phase sequences of the two intersections. Finally, the last variable is used to generate offset.

{ f_1 ; f_2 ; f_3 ; f_4 ; f_5 ; f_6 ; f_7 ; f_8 ; f_9 ; f_{10} ; f_{11} ; f_{12} ; f_{13} ; f_{14} } {101101;11101;01010;11111;00010;10100;11110;01100;11111;01000;10100;1100;1110;101111}

A cycle length is determined in the following manner. Suppose that the minimum cycle length and maximum cycle length are 50 and 120 seconds, respectively. The first variable corresponds to the cycle length. A fractional value (f_I) for cycle length, 0.714, is obtained as follows:

 $\{101101\}_2 = \{45\}_{10}$ $f_1 = 45 \div 63 = 0.714$ since the range of 6 digits binary code is $[0 ... 2^6 - 1]$.

$Cycle = MinC + INT [(MinC - MaxC) \times f_1]$ where							
MinC	=	minimum cycle length (sec);					
MaxC	Ξ	maximum cycle length (sec); and					

=

fraction value.

From Equation 9 and the first fraction value of 0.714, a cycle length of 100 seconds is obtained.

The green times of the main street and cross street are determined from the second variable, $\{11101\}_2 = \{29\}_{10}$. In a similar way, f_2 of 0.935 (= 29 ÷ 31) is obtained. A main street green time of 71 seconds and a cross street green time of 29 seconds are determined from the Equations 10 and 11, respectively.

Green _{MAIN} =	mp ₁ (10se	c) + $mp_2(15sec)$ + INT [($Cycle - MP$) × f_2]	(10)
Green _{CROSS} =	<i>mp</i> ₃ (10s	ec) + $mp_4(15sec)$ + INT [($Cycle - MP$) × $(1 - f_2)$]	(11)
where			
MP	=	sum of minimum phase time (50 sec); and	

Max $(mp_1+mp_2+mp_3+mp_4, mp_5+mp_6+mp_7+mp_8)$.

Green times (ϕ_1 and ϕ_2) are determined from Equations 12 and 13 by using the third variable, $\{01010\}_2 = \{10\}_{10}$. Since f_3 is 0.323 (10 ÷ 31), green times of phases 1 and 2 are determined as 25 and 46 seconds, respectively.

$$Green (\phi_1) = mp_1(10sec) + INT [((Cycle - MP) \times f_2) \times f_3]$$

$$Green (\phi_2) = mp_2(15sec) + INT [((Cycle - MP) \times f_2) \times (1-f_3)]$$
(12)
(13)

Other green times can be determined in a similar manner. The phase sequence of intersections one and two are determined from the 12th and the 13th variables, respectively. Because each intersection has 16 possible phase sequences and a four digit

(9)

binary code can represent numbers from 0 to 15, the phase sequence can be determined on the basis of a four digit binary code. In this example, $\{1100\}_2 = \{12\}_{10}$ and $\{1110\}_2 = \{14\}_{10}$ represents (lead-lead-lag-lag) and (lag-lead-lag-lag), respectively.

Finally, offset is determined from Equation 14. In this example, the 14th variable, $\{101111\}_2 = \{47\}_{10}$, is equal to 0.746 (47 + 63). An offset of 74 seconds is obtained by using Equation 14.

Offset = INT [Cycle
$$\times$$
 f₁₄]

(14)

Mesoscopic Simulator

As a part of the proposed GA-based signal optimization program, a mesoscopic simulation program was developed to provide a function value (i.e., fitness value) to the GA optimizer for each potential solution. The mesoscopic simulator is an intermediate product of macroscopic and microscopic simulation, and it is designed to model queue blocking effects and provide more realistic delay estimates.

Components

Arrival pattern

Previous research suggests that the random arrival flow (Poisson) is sufficient in the case of external approaches that do not have a signal within two minutes of travel time to the subject approach (18). However, it was felt that an application of Poisson distribution would cause unrealistic results. For example, suppose vehicle arrivals are generated every second. A Poisson distribution could generate two or more vehicles in a second, and that is certainly not realistic. Thus, the Binomial process is used in this research to generate the external vehicle arrival patterns. That is, vehicle arrivals of external movements are assumed to follow the Binomial distribution as an approximation of the Poisson distribution (19).

Initialization

In order to prevent biased results, a network initialization process is essential. The main purpose is to obtain initial queue lengths. The mesoscopic simulator runs a certain period of initialization before it starts an evaluation run. This is similar to other simulation programs. For example, CORSIM initializes until either the network reaches an equilibrium condition or a certain predetermined time ends (20). It is noted that the TRANSYT-7F program also employs an initialization period.

Saturation flow rate

Numerous factors affect the saturation flow rate. The saturation flow rate model of NCHRP report 3-47, based on field data collected in over 5,000 cycles of oversaturated conditions, was adopted in this research (18). The model uses adjustment factors such as the distance to the back of queue, traffic pressure or headway compression, the radius of travel path, and signal timing (g/C).

Vehicle departures

Vehicles are discharged from the queue at a saturation flow rate during the effective green time unless queue blocking occurs due to spillback from a downstream signal. Discharged vehicles are further divided into three types of vehicles: left-turn, through, and right-turn vehicles based on predetermined turning propensities. It is reasonable to assume that the turning percentages at the downstream intersection can be different depending on the upstream movements. Thus, three turning percentage vectors per intersection are used, one for each upstream movement instead of just one turning percentage vector.

Queue evolution model (End of Queue model)

The traditional queue polygon model, which is based on the input-output model, moves the whole queue platoon together following onset of green as if the platoon were a train. The proposed queue evolution model, shown in Figure 3, divides interior link flows into three stages: saturation density, jam (queued) density, and free density. The end of queue (EOQ) traces the end of the jam density position, while the end of saturation (EOS) traces the end of saturation density position. The speeds of EOQ and EOS movements are based on macroscopic shock wave theory. During downstream red time, the EOS and EOQ are equal to zero and the queue length, respectively. At the onset of effective green, the EOS starts moving upstream while the EOQ continues to grow with vehicle arrivals until the EOS reaches the EOQ at point B in Figure 3.



FIGURE 3 Queue evolution model.

Queue blocking

For interior links, the EOQ is continuously examined to check for the occurrence of queue blocking. Queue blocking occurs when the EOQ exceeds subjective link length.

Delay calculation

It is assumed that the time-space diagram can be divided into three regions: jam density (stopped delay), saturation flow density (reduced speed delay), and free flow density (no delay). The area of polygon ABC (in Figure 3) yields stopped delay while the area of polygon BCD represents the delay due to reduced speed between free flow speed and saturation flow speed. The total delay during the cycle length is obtained from the following equation.

$$TD = Polygon \ ABC + \left(\frac{u_f - u_s}{u_f}\right) Polygon \ BCD$$
(15)

where

 $\begin{array}{rcl} TD & = & \text{total delay (veh-sec);} \\ u_f & = & \text{free flow speed; and} \\ u_s & = & \text{saturation flow speed.} \end{array}$

The average delay is computed by dividing the total delay by the number of vehicles departed. No macroscopic delay formula, such as random-plus-oversaturation delay, is used because the mesoscopic simulator uses Binomial arrival patterns and multiple-cycle simulation to account for incremental delays due to random arrivals, overflows and nonzero queue at the start of the analysis period.

Limitations

The mesoscopic traffic simulator simulates arterial systems, including diamond interchanges. It explicitly models link blockage due to spillback but does not presently consider intersection blockage to cross flow traffic. In other words, during queue blocking or spillback conditions, the intersection area remains clear such that cross street movements are not blocked. Left-turn bay blockage due to either heavy left turn movements or through movements is also not explicitly modeled.

EXPERIMENTAL DESIGN

The genetic algorithm-based signal optimization program is implemented at two closelyspaced intersections. Both undersaturated and oversaturated conditions are considered for evaluation. CORSIM simulation program is used to evaluate delay estimates of the mesoscopic simulator.

Geometric Design

Two closely-spaced signalized intersections with 100 meters of interior spacing are considered in this experiment. The geometry of the experimental site and traffic demand volumes are shown in Figure 4 and Table 1, respectively. In the case of oversaturated conditions, the volume-to-capacity ratio (i.e., degree of saturation) was around 1.2 for most movements at the intersections. It is noted that only through and left-turn movements are considered for simplicity of model design.



FIGURE 4 Geometry of experimental site.

Genetic Algorithm Design

The genetic algorithm requires that certain input parameters be set such as the maximum number of generations, number of individuals, crossover probability, and mutation probability. One study indicates that a crossover probability that is too high could destroy good solutions faster than their production, while a crossover probability that is too low may inactivate the search process (21). In addition, a small value of mutation probability is always used because a high value of mutation probability is essentially equal to a random search. In this paper, the GA optimizer utilized up to 250 generations with a population size of 10 per generation, a crossover probability of 0.4, and a mutation probability of 0.03. The previous study shows that the solutions are not sensitive to the moderate parameter values used in this study (22). An elitist technique is used to guarantee that the best solution of the current generation transfers to the next generation (16). In this experiment, the initial individuals are randomly generated. However, it is noted that the previous signal timing plan can be used as one of initial individuals.

Demand (vph)	Int.	Northbound		Southbound		Eastbound		Westbound	
	number	LT	TH	LT	TH	LT	TH	LT	TH
undersaturated	1	150	300	150	300	150	300	90	360
	2	150	300	150	300	90	360	150	300
oversaturated	1	300	600	300	600	300	600	180	720
	2	300	600	300	600	180	720	300	600

TABLE 1 Traffic demand for under/oversaturated conditions

Simulation Model Design

In this study, simulation runs are performed for a 15 minute duration. The 15 minute time period is chosen to correspond with the *Highway Capacity Manual* (HCM) analysis duration. To obtain initial queue lengths, three minutes are used for an initialization period. It is assumed that three minutes are sufficient for any single vehicle to pass unimpeded through the system.

It is noted that the parameters used in this experiment, including saturation flow rate, queue discharge headway, start-up lost time, and queue storage capacity per vehicle are obtained from NCHRP report 3-47 which utilized more than 5,000 cycles of oversaturated conditions.

MESOSCOPIC SIMULATOR EVALUATION

In this section, the mesoscopic simulation program is evaluated. First, the queue evolution model for queue blocking model is examined. Second, the CORSIM simulation program is used to evaluate the mesoscopic simulator.

Queue Evolution Model

A graphical example of the queue evolution model is shown in Figure 5. At the beginning of the onset of downstream intersection effective green time, queue length may decrease at a rate of saturation flow minus arrival flow. However, the end of queue (EOQ) position will be increasing until the platoon wave reaches the end of queue position. It is important to note that the tradition input-output queue model would fail in detecting queue blocking in this case.





Even though average delay comparison results for oversaturated conditions are not provided in this paper, they revealed some differences due to the different calculation approaches. CORSIM does not appear to account for remaining queue in calculating average delay while the mesoscopic simulator does. Thus, queue time was used for oversaturated conditions as a surrogate of average delay. Queue time obtained from the mesoscopic simulator is compared to the 95% confidence interval of CORSIM simulation results. As shown in Figure 6 (b), queue time matches well except for the northbound movement at intersection 1 (I-NB).

GA OPTIMIZER EVALUATION

Convergence of GA Optimizer

The minimum objective function value of with and without the elitist technique is plotted in Figure 7. The GA optimizer may not improve the objective function value between generations. Thus, an elite algorithm is usually used to guarantee that the best solution of the current generation transfers to the next generation. In this research, the best solution is kept for each generation and then substituted for the worst individual if the best solution is disrupted during evolution. The most significant improvement of the objective function value occurred within 100 generations.



Interpretation of Schema Theorem

Assuming that the schema theorem and building block hypothesis hold, the proposed GAbased program should search for better signal timing plan parameters in subsequent generations, including cycle length, phase sequences, green splits, and offsets. In this experiment, the GA-based program evaluated 2500 signal timing plans (10 signal timing plans per generation \times 250 generations).

In Figure 8, the bar graph depicts the number of signal timing plans examined for each cycle length, while the line graph provides the minimum of average delays found from each cycle length. The GA-optimizer found optimal cycle lengths of 53 and 115 seconds for undersaturated and oversaturated conditions, respectively. The GA optimizer has evaluated around 1000 signal timing plans for those near-optimal cycle lengths. This indicates that GA optimizer attempted to find better solutions by alternating the other parameters such as green splits, phase sequences, and offsets. It is noted that the minimum of average delays curve is almost flat for certain ranges of cycle length indicating multiple near optimal solutions.



(a) Undersaturated conditions.





(a) Undersaturated conditions



(b) Oversaturated conditions

Figure 9 Delay-different-of-offset vs. GA optimizer

DISCUSSION OF RESULTS

The queue evolution model developed in this research is especially important for the optimization of oversaturated closely-spaced signalized intersections. At times, the traditional input-output queue model tends to underestimate the end of queue position such that queue blocking model could allow more vehicles than actual capacity.

The interpretation of genetic algorithm optimizer indicates that the GA optimizer searches more frequently for a good cycle length range. The exhaustive offset search shows that the GA optimizer found an acceptable solution. In terms of computation time, it takes about 9.1 minutes for two intersections with a Pentium 133MHz (32MRAM) computer.

The delay estimates of the mesoscopic simulator and CORSIM program seem to match well for undersaturated conditions. However, the analysis showed some discrepancies for oversaturated conditions. This is because CORSIM does not account for remaining queue in calculating average delay. Consequently, queue time is used as a surrogate for average delay. As shown in Figure 6, queue time between the mesoscopic simulator and CORSIM still indicates differences. This is because of intersection blockage which is modeled explicitly during CORSIM simulation run. In other words, once link blockage occurs vehicles block intersection area such that the cross street movements are completely blocked until intersection area becomes clear. This is because CORSIM considers a link as the distance from upstream stopline to downstream stopline. Therefore, some caution should be given to the use of queue time as an MOE. It should be noted that the spillback probability (record type 141 in CORSIM input) fails to prevent intersection blockage.

CONCLUSIONS AND RECOMMENDATIONS

In this paper, a GA-based signal optimization program, which simultaneously optimizes four traffic signal parameters (i.e., cycle length, green split, offset, and phase sequence) during oversaturated conditions, is developed. The evaluation results of the mesoscopic simulation program show that both average delay and queue time obtained from the mesoscopic simulator and CORSIM match well for undersaturated conditions. During oversaturated conditions, average delays obtained from CORSIM should be used with caution because average delays are based on the vehicles departed from the subject link. In other words, remaining queue is not accounted for in its average delay. Thus, queue time should be used for oversaturated conditions. It is recommended for CORSIM that intersection blockage should be preventable as a simulation option.

It is found that the proposed GA-based program provides acceptable solutions within reasonable amount of time. The computation time could be reduced by a using good initial timing plan. For example, the previous signal timing plan can be used as a starting point for the GA optimizer. This certainly will speed up the convergence of the GA optimizer.

This paper represents an initial study of a new traffic signal optimization technique. The evaluations performed in this paper are very limited in scope. Thus, further evaluation and validation study for wider ranges of traffic demands and geometric conditions should be conducted.

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