Evaluation of Stochastic Optimization Methods of Traffic Signal Control Settings for Coordinated Actuated Signal Systems

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ABSTRACT

Since Webster developed the principle of traffic signal control optimization theory in late 1950, the field of traffic signal timing control has advanced dramatically for the past a few decades. These include coordinated actuated control and adaptive control on the basis of advances in the detection and communication technologies. However, the existing traffic signal timing optimization program still focuses on the basic four parameters (i.e., cycle, green split, offset, and phase sequence). In addition, these optimization programs do not consider stochastic variability in drivers' behavior and vehicular inter-arrival times, vehicle mix, and so forth. Even though a few research efforts focused on the use of stochastic simulation models, little research was done in the optimization of traffic signal controller settings (e.g., minimum green time, vehicle extension time, minimum vs. maximum recalls) and detector settings (e.g., location and pulse vs. presence modes).

This paper presents a stochastic traffic signal optimization method that consists of stochastic simulation model and an external optimizer. Three widely-used optimization methods (i.e., genetic algorithm, simulated annealing and OptQuest engine) were considered and tested their performance using test networks. The performance of the proposed stochastic optimization method was compared with existing optimization programs including TRANSTY-7F, and the SYNCHRO under microscopic simulation environment. The results indicate that the proposed method outperformed existing programs in the optimization of the basic four parameters, and also showed that additional controller and detector settings can further improve the operations of coordinated actuated signal control systems.

INTRODUCTION

The traffic signal is one of the most common facilities being operated by traffic engineers to control traffic in an orderly manner. Traffic signal control settings optimization (a.k.a., traffic signal timing optimization) has been recognized as one of the most cost-effective methods for improving accessibility and mobility at signalized arterials and networks. Thus, traffic engineers always wanted to achieve better operation of traffic signal control, while researchers focused on the development of efficient methods for traffic signal control settings optimization.

In order to optimize signal control settings, a variety of macroscopic optimization software, including SYNCHRO (*1*), TRANSYT-7F (*2*), and PASSER™ V-03 (*3*), has been developed and widely used across the United States. The macroscopic models are computationally fast and simple in input requirements. However, these models are limited in reflecting various drivers' behaviors, interaction between running vehicles and variability in demands (*4*). As such, a recent version of TRANSYT-7F (T7F) introduced a genetic algorithm (GA) coupled with a microscopic traffic simulation program CORSIM to overcome those demerits of the macroscopic optimization models. In addition, existing optimization programs are limited to only four traffic signal timing parameters (i.e., cycle length, green splits, phasing sequences and offsets). Actually, additional traffic signal control settings such as detector length, minimum green and vehicle extension can play important roles in the efficiency of actuated signal control systems. Foy *et al.* (*5*) introduced a GA in the determination of signal timing for a two-phase system in 1992. Hadi and Wallace (*6*) investigated the use of a GA in combination with the T7F optimization routine to select signal timing (cycle length, green splits and offsets) and signal phasing. They concluded that a GA has the potential of optimizing signal timing and phasing. Park *et al*. (*4*) developed a stochastic signal optimization method using GA interfaced with the microscopic simulation program CORSIM to optimize cycle length, green splits, and offsets simultaneously for a pre-timed traffic signal system. Park and Schneeberger (*7*) expanded the method to a coordinated actuated traffic signal control system to optimize offsets, and compared the results with those of SYNCHRO and T7F as well as the existing timing plan. In their research, a GA with the microscopic simulation program VISSIM was used.

Given the successful applications of microscopic simulation model-based stochastic optimizations, this research investigates various optimization methods and expands stochastic optimization into additional traffic signal control settings. Thus, the objectives of this paper are to (i) develop a stochastic optimization method that can consider not only basic four traffic signal control parameters (i.e., cycle, split, offset and phase sequence) but also controller and detector settings, and (ii) evaluate the proposed approach by comparing with existing programs under a microscopic simulation environment.

The remainder of this paper is as follows: the methodology section provides the selection of microscopic simulation model, descriptions of stochastic optimization methods, traffic signal control optimization variables and objective function. Test networks used in the optimization and evaluation are presented, followed by results. Finally conclusions and recommendations are provided.

METHODOLOGY

This section covers the selection of adequate microscopic simulation model as well as suitable optimization methods, and then discusses the optimization variables and objective functions used in this study.

Microscopic Simulation Model Selection

Microscopic simulation models widely used in the United States are CORSIM, VISSIM, PARAMICS and SIMTRAFFIC. Among these, this study selected CORSIM because of its long history of development and support from FHWA, its capability of modeling common U.S. traffic signal controllers (e.g., NEMA or Type 170 controllers), and its fast simulation run time compared to other models. Park and Yun (*8*) compared various microscopic traffic simulation models, including PARAMICS, VISSIM, CORSIM and SIMTRAFFIC in terms of computation time and the capability of modeling a coordinated actuated signal control system. CORSIM was the fastest in simulation run time and is equipped with built-in traffic signal control logic for the coordinated actuated signal control system. VISSIM and PARAMICS can mimic the traffic signal control system using an external program such as VAP and API respectively. Actually, the VISSIM program provides the VAP program and example codes, and several users of PARAMICS have developed the API for actuated signal control systems in the United States (*8*). However, users are required to develop their own program codes in order to realize advanced features of actuated signal controllers such as volume-density mode. SIMTRAFFIC was computationally the most expensive among these models. Even though CORSIM was selected, it is noted that it can only emulate basic traffic signal controller features. However, since the purpose of this study is to demonstrate whether optimization of additional traffic controller and/or detector settings can improve the operations of a coordinated actuated traffic signal control system, it should be reasonable to implement CORSIM for this study.

Stochastic Optimization Methods

It is noted that traditional optimization methods (i.e., Newton or conjugate gradient methods) which require a closed-form function to find directions for the next movement, are not applicable for microscopic simulation-based stochastic optimization because microscopic simulation models do not provide such a function. Thus, heuristic optimization methods have to be adopted. Three commonly-used optimization methods: a GA, simulated annealing (SA) and a commercial optimization program OptQuest engine were chosen. Brief descriptions of these methods are presented in this section.

Genetic Algorithm

The genetic algorithm (GA) was developed by John Holland in the early 1970s at the University of Michigan (*9*). GA makes up a family of computational models inspired by evolution (*10*). The GA encodes a potential solution for a specific problem into simple chromosome-like data structures and applies recombination operators to the structures so as to preserve critical information. It has been used to solve problems with objective functions that are difficult to work out with mathematical approaches (*9,11,12*). GA manipulates a population of potential solutions and implements a "survival of the fittest" concept to search for better solutions (global solutions). This provides an implicit as well as explicit parallelism (*13*). Explicit parallelism allows for the exploitation of several promising areas of the solution space at the same time through generations. The implicit parallelism is due to the schema theory developed by Holland (*9*). GA has been shown to solve linear and nonlinear problems by exploring all regions of search space and exponentially exploiting promising areas through selection, crossover and mutation operations (*14*).

Simulated Annealing

Simulated annealing (SA) was first introduced by Metropolis *et al*. (*15*). SA is based on the analogy between a stochastic search for a minimum in a system and the physical annealing process in which a metal gradually cools into a minimum crystalline structure with minimum energy (*16*). The application of SA for deterministic optimization problems was introduced by Kirkpatrick *et al*. (*17*). As an analogy of the annealing process for a thermodynamic system, SA firstly determines an initial energy level (*E)* at an initial high temperature (*T*). By perturbing the initial set of optimization variables for the system at a constant temperature, SA keeps computing the change in energy (*dE)*. When the energy decreases the new configuration becomes the next search point. Even though the energy increases, SA determines the acceptance of the new configuration with a probability given by the Boltzmann factor [*exp -(dE/T)*], which becomes smaller as temperature decreases according to the annealing schedule. The perturbation is repeated until SA achieves good sampling statistics for the current temperature, and then SA reduces the temperature (cooling). Based on the above process, SA is able to avoid getting stuck in local minima to find the best objective function value by accepting a new search point that increases the objective value as well as a search point that decreases it. Generally, the escape from local minima in SA is dependent on the annealing schedule, the choice of initial temperature, and the number of perturbations at each temperature, and the amount of temperature reduction (*18*).

OptQuest Engine

OptQuest engine is commercial optimization software developed by Fred Glover in OptTek Systems Inc. (*19*). The OptQuest engine integrated Tabu search, scatter search, integer programming, and neural networks into a single search algorithm for deterministic or stochastic optimization problems. Especially, neural network plays a role to guide the search for best solutions. In addition, it remembers good solutions and recombines them into new solutions in order to avoid getting trapped in local minima cased by a noisy model (*20*). The OptQuest engine is in the format of a Windows dynamic linked library (DLL) for the use with Visual Basic, C, COM, C++, .NET, and Java applications so that the user-written application is necessary to evaluate each solution generated by OptQuest engine (*20*). OptQuest®, a software version of OptQuest engine, has been embedded in several commercial programs or simulation software such as CrystalBall (*19*), and Arena (*21*), as an optimization module.

Optimization Variables

The traffic signal control settings (i.e., optimization variables) for a coordinated actuated signal control system are divided into three groups based on the characteristics of those variables as shown in Table 1 (*1,22,23*). It is noted that Group 3 variables relating to volume-density mode of operation can be selectively applied to those approaches with speed limits of 35 mph or higher (*24*).

Table 1. Optimization Variables by Groups

Group	Characteristics	Variables Included
Group 1	- Always required by controllers - Four major signal control settings affecting the operational capacity of signal systems - Common optimization variable in SYNCHRO and T7F	- Cycle length - Green splits - Offsets - Phasing sequences
Group 2	- Always required by controllers - Controller and detector related settings - Affect the operational efficiency of signal systems	- Minimum green - Recall - Vehicle extensions - Detector placements - Delayed call - Extended call
Group 3	- Volume-density mode of operation related settings - Affect the operational efficiency of signal systems	- Minimum initial - Maximum initial - Time / actuation - Time before reduce - Time to reduce - Minimum gap

During stochastic optimization, the traffic signal control settings (i.e., optimization variables) have to meet various constraints such as minimum green time requirement, barriers, equality requirement between cycle length and the sum of green times, etc. Thus, it is practical to adopt a decoding scheme such that optimization variables reside within a feasible region during optimization. This study adopted a fraction-based decoding scheme, which was introduced by Park *et al*. (*25*) for Group 1 variables. The decoding scheme allows all Group 1 variables to be feasible during the optimization. It is noted that the force off points and permissive periods, needed for coordinated actuated signal control, are calculated from the optimal green splits and phase sequence obtained during the stochastic optimization. The same decoding scheme is applied to all three stochastic optimization methods.

For the optimization variables in Groups 2 and 3, there were neither critical dependencies nor strict constraints. Thus, minimum and maximum values were assigned to each optimization variable such that each variable resided within the feasible region during the optimization.

Objective Functions

The CORSIM simulation program provides various system-wide performance measures such as queue time, delay, throughput, stop time, etc (*23*). Since the objective function should adequately capture the performance of traffic signal control settings, the selection of objective function is critical. In this study, stochastic optimization methods use either total queue time (vehicle-minutes) or average of control delay (seconds per vehicle) as an objective function (or evaluation function) depending on the characteristics of optimization variable groups as shown in Table 2.

Table 2. Objective Functions and Characteristics

Objective Function	Optimization Variables	Characteristics
Queue Time, vehicle-minutes	Group 1	- Queue times experienced by not only discharged vehicles from link but vehicles currently on the link - Prevents improperly short green splits and resulting congestion - Cumulative value - Stochastic variability is relatively big
Control Delay, seconds per vehicle	Group 2 Group 3	- Control delay experienced by only discharged vehicles from link - Stochastic variability is relatively small such that it is adequate to evaluate improvements of operation in signal system by optimizing Group 2 and Group 3 variables - Average value

In CORSIM, the control delay of each vehicle is calculated once the vehicle completes its trip through the link, whereas queue time from the CORSIM simulation is calculated from both vehicles discharged from the link and vehicles remaining on the link (*23*). During the optimization of Group 1 variables, inadequate values of the optimization variables could be evaluated during the optimization process, and possibly result in extreme congestion. When this happens, the control delay would not reflect the impacts of the congestion because queued vehicles still remaining on the link are not used in the delay calculation. Thus, the queue time is used as an objective function for Group 1 variables optimization, even though control delay is intuitive and easily understood. It is noted that control delay measures from the optimal timing plans are reasonably evaluated. On the contrary, the average of control delay is selected as an objective function for Group 2 and Group 3 variables. Group 2 and Group 3 variables are optimized separately under optimal Group 1 variables, and the change in the capacity of the intersection by optimizing these variables is relatively small compared to optimizing Group 1 variables.

Given that microscopic simulation models at times show quite significant variability in their performance measures, it is crucial to control (or reduce) such variability during the optimization. If such variability is not properly controlled, the optimization could be oscillating a lot and may not be converging. Thus, five random-seeded CORSIM runs were conducted and the median value was obtained as an objective function value during the optimization.

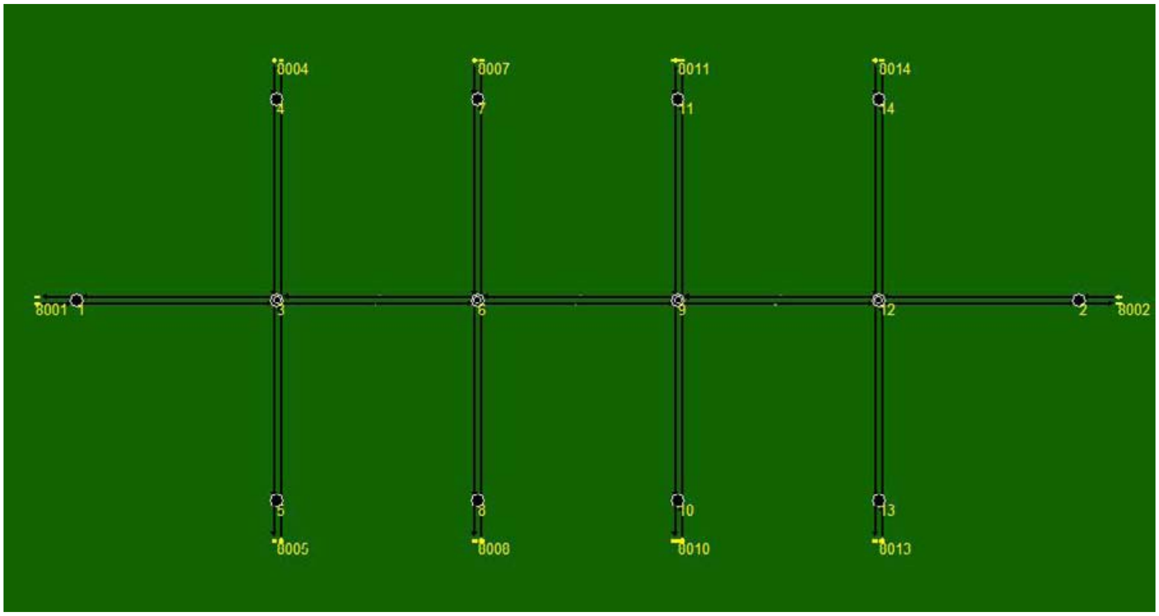
TEST NETWORK

A total of six test networks were designed to represent various operational conditions of coordinated actuated signal systems. These networks are divided according to traffic demands and network layouts (linear network vs. grid network) as shown in Table 3. Especially, the "heavy left-turn traffic" and "heavy traffic" are prepared to reflect the congestion caused by the left-turn bay spill-over. It is noted that the detector layouts including size and placement were chosen based on the guidelines of the *Traffic Control Systems Handbook* (*22*).

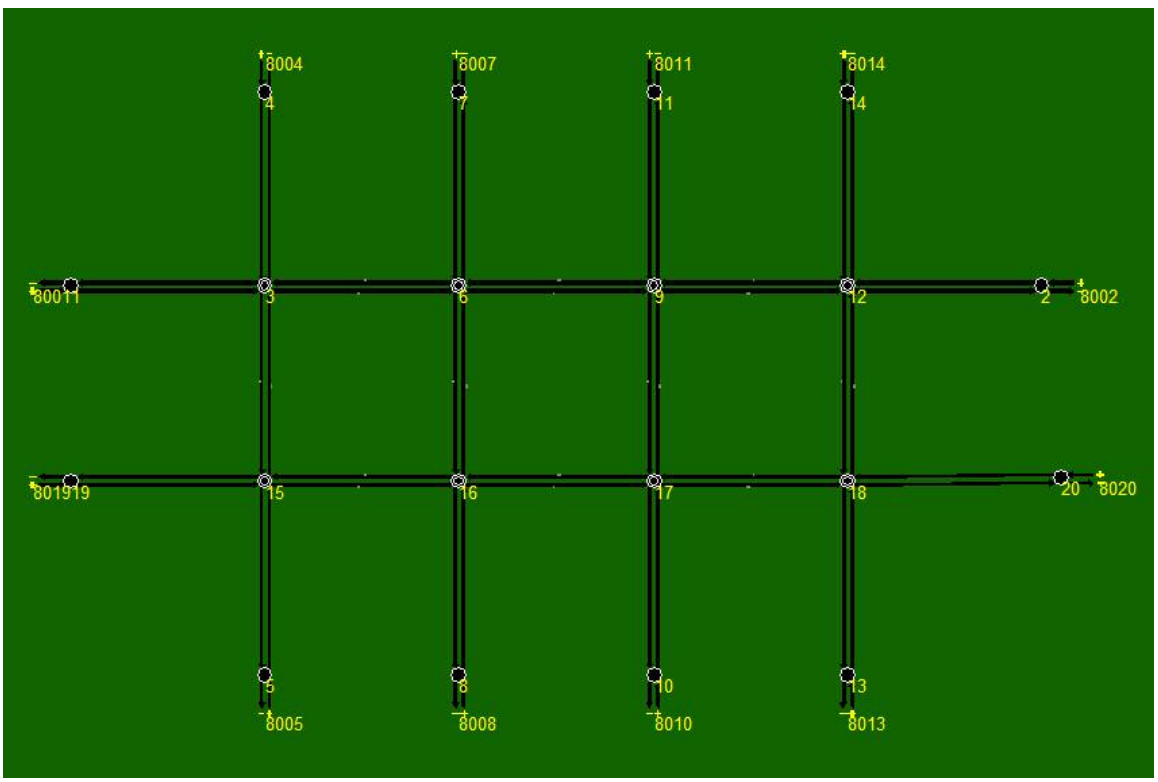
Table 3. Test Network Identification

Traffic Demand	Network Layout	
	Network A: Linear Network (4 Intersections)	Network B: Grid Network (8 Intersections)
Light Traffic	V1NA	V1NB
Heavy Left-turn Traffic	V2NA	V2NB
Heavy Traffic	V3NA	V3NB

Figures 1 and 2 show the layouts of networks and detectors deployed in the test networks



(a) Network A (Linear Network)



(b) Network B (Grid Network)

Figure 1. Network Layout

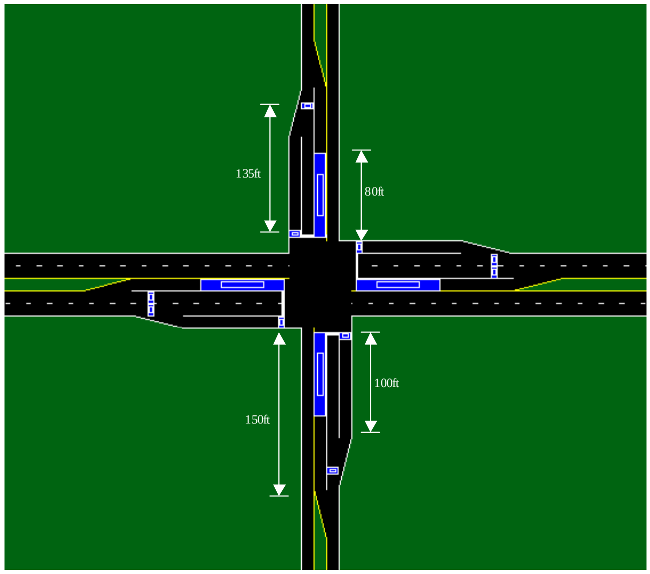


Figure 2. Examples of Intersection Geometry and Detector Layout
Notes (1) Eastbound and Westbound major approach, (2) all detectors in presence mode, and (3) detectors in the major (coordinated) approaches are installed for data collection.

These networks were built in SYNCHRO (Version 6 – Build 612), T7F (Version 10.2) and CORSIM (TSIS Version 5.1) (*1*,*2*,*23*). Significant efforts were given to develop comparable networks across these three programs. In addition, it was found that the use of hypothetically long approach links in CORSIM networks could prevent a simulation result where vehicles were rejected to enter the network due to a long queue reaching to the vehicle entry points.

COMPARISON OF TRAFFIC SIGNAL CONTROL SETTINGS

Implementation of Stochastic Optimization Methods

In order to implement the proposed stochastic optimization methods, an interface between the optimization engine and the microscopic simulation program, CORSIM was developed. The interface which is written in C++ program and MATLAB m-file works as follows: firstly, the optimization engine generates a population of solutions or single solution according to its solution generation method. Secondly, the interface program produces an input file for the CORSIM simulation based on the solution from the optimization engine, and then conducts five CORSIM simulation runs. Finally, the interface extracts an objective function value from the CORSIM output files and then transfers it to the optimization engine. This process continues until the termination condition is met. The stochastic optimization methods stop at the maximum iteration number of 2,500 to make fair comparisons. For the GA-based optimization, a population size of 100 and a maximum generation of 25 were used (*26*).

Once optimal control settings were found, 100 multiple CORSIM simulation runs were made to consider stochastic variability. The mean and standard deviation (STD) of queue time and control delay are presented for comparison purposes. Network B is initially used for Group 1 variables optimization to verify the performance of the three stochastic optimization methods, while Network A is used for Groups 2 and 3 variables optimizations to examine the effect of selected signal control settings (refer to Table 3and Figure 1).

Group 1 Variables Optimization

In order to establish baseline performance of the stochastic optimization methods, both T7F and SYNCHRO, arguably the most widely-used signal timing optimization programs in the U.S., were implemented. The T7F program provides three basic optimization options and its combinations. Therefore, this research tested the performances of various optimization options available in T7F as follows:

(1) Hill-Climbing method with macroscopic simulation,
(2) GA with macroscopic simulation,
(3) GA with microscopic simulation model CORSIM (a.k.a., CORSIM-direct optimization), and
(4) GA with macroscopic simulation + CORSIM-direct optimization.

It is noted that the third option does not optimize phase sequences, while the second option provides phase sequence optimization. In order to find the best timing plan, the fourth option combined the second and third options. In other words, it first employed optimal phase sequences optimized by the second option, and then optimized remaining signal timings using the third option.

As shown in Table 4, the CORSIM-direct optimization produced the best performance. Similar results were found from V2NB and V3NB networks.

Table 4. Summary of T7F Optimization Results in V1NB Network

Type of Simulation and Optimization		Queue Time (STD), vehicle-minutes	Control Delay (STD), seconds per vehicle	Remarks
Macroscopic Simulation	1. Hill-Climbing	1,621.73 (86.28)	16.41 (0.79)	
	2. GA	1,893.93 (93.93)	19.36 (0.85)	- Population: 99 - Generation: 25
Microscopic Simulation	3. GA	1,033.55 (30.44)	11.35 (0.29)	- No phasing sequence - Population: 99 - Generation: 25
Macroscopic + Microscopic Simulations	4. GA	1,294.33 (98.07)	13.88 (0.87)	- Phasing sequence from GA using Macroscopic simulation - Population: 99 - Generation: 25

Note: T test shows that the third optimization result is significantly better than that of the fourth optimization at a significant level of 0.05

Figure 3 shows the best solutions obtained by the three proposed stochastic optimization methods for Network B. Apparently the GA converges to the lowest queue time, while the SA and the OptQuest engine converged to similar solutions. The fundamental difference between the GA-based method and CORSIM-direct optimization should be noticed. T7F conducts the optimization of the signal timing plan in a coordinated actuated signal control by manipulating only force-off points and the minimum splits work as constraints in the optimization (*2*). However, the GA-based method calculates green splits first based on the minimum splits as well as phasing sequences generated by GA, and then determines resulting force-off points and permissive periods.

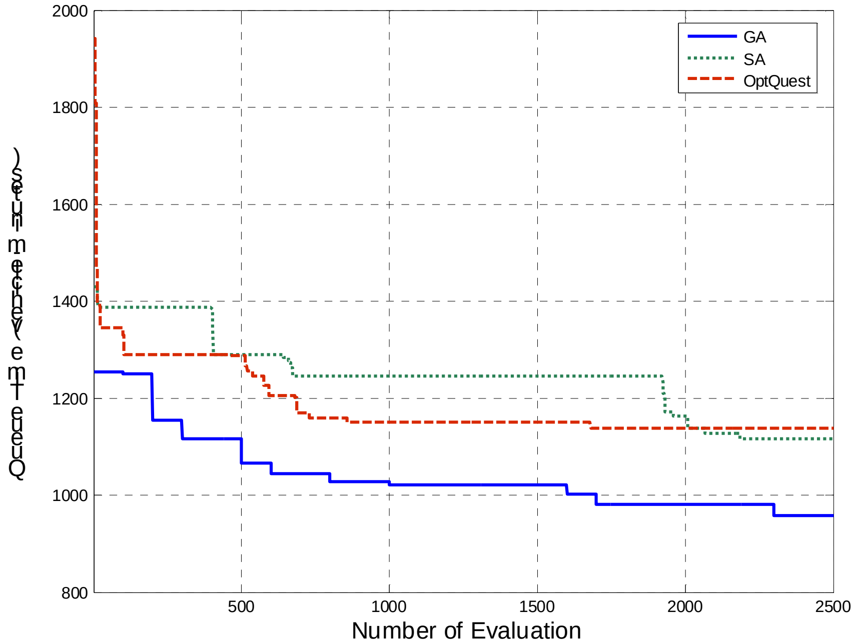


Figure 3. Convergence of Three Optimization Methods in V1NB Network

Tables 5, 6 and 7 summarize the optimization results of the five methods including T7F and SYNCHRO using the grid network (Network B) under three different traffic demands. It is noticed that queue times shown in Figure 3 may appear different from those in Tables 5 and 6. The values in Figure 3 were achieved from the results of three optimization methods using five random-seeded simulation runs while the figures in Tables 5 and 6 were calculated from 100 random-seeded simulation runs using signal timing from the optimization methods.

Table 5. CORSIM Evaluation Results Using V1NB Network (Light Traffic Condition)

Type of Optimization		Queue Time (STD), vehicle-minutes	Control Delay (STD), seconds per vehicle
SYNCHRO		1,236.90 (36.29)	12.79 (0.35)
T7F (CORSIM-direct Optimization)		1,033.55 (30.44)	11.35 (0.29)
Stochastic Optimization Method	GA	991.49 (37.55)	10.80 (0.38)
	SA	1,193.43 (51.84)	12.75 (0.53)
	OptQuest	1,263.78 (65.99)	13.64 (0.68)

Note: T test shows that the result of GA-based optimization method is significantly better than that of T7F (CORSIM-direct optimization) at a significant level of 0.05

In the light traffic network (V1NB), the GA-based stochastic optimization method achieved the best solution among the five methods for Group 1 variables (see Table 5).

In the congested networks (V2NB and V3NB), the GA-based stochastic optimization method consistently performed better than other methods. Even though the CORSIM-direct optimization method integrates the CORSIM simulator and the GA as in the GA-based stochastic optimization method, one limitation of the CORSIM-direct optimization method was its incapability to optimize phase sequences. Apparently, the feature of phase sequence optimization can significantly improve the performance of the congested network as shown in Table 7.

Table 6. CORSIM Evaluation Results Using V2NB Network (Heavy Left-Turn Traffic)

Type of Optimization		Queue Time (STD), vehicle-minutes	Control Delay (STD), seconds per vehicle
SYNCHRO		5,710.68 (421.17)	44.19 (2.83)
T7F (CORSIM-direct Optimization)		3,577.16 (265.26)	29.47 (2.05)
Stochastic Optimization Method	GA	3,448.84 (300.03)	28.42 (2.29)
	SA	4,430.43 (383.11)	35.57 (2.77)
	OptQuest	3,641.27 (241.13)	29.93 (1.88)

Note: T test shows that the result of GA-based optimization method is significantly better than that of T7F (CORSIM-direct optimization) at a significant level of 0.05

Table 7. CORSIM Evaluation Results Using V3NB Network (Heavy Traffic)

Type of Optimization		Queue Time (STD), vehicle-minutes	Control Delay (STD), seconds per vehicle
SYNCHRO		11,680.96 (604.78)	69.83 (4.03)
T7F (CORSIM-direct Optimization)		10,821.32 (650.20)	64.67 (4.07)
Stochastic Optimization Method	GA	7,455.82 (329.27)	45.66 (2.13)
	SA	8,619.05 (631.88)	56.61 (5.50)
	OptQuest	9,358.43 (694.75)	56.60 (3.90)

Note: T test shows that the result of GA-based optimization method is significantly better than that of the SA method at a significant level of 0.05

Group 2 and Group 3 Variables Optimization

Group 2 and Group 3 variables can affect the efficiency of coordinated actuated signal systems by reducing unnecessary green times of actuated phases, and transmitting saved green times to the coordinated phases (*22*). However, given that the amount of green times assigned to non-coordinated phases are relatively low, the optimization of these variables would have relatively small benefits compared to Group 1 variables.

Before implementing optimizations for Group 2 and Group 3 variables at a new linear network (see Figure 1(a)) with three different volume levels, this study optimized Group 1 variables using the SYNCHRO and GA-based stochastic optimization method. The results of Group 1 variables optimizations by these two methods would validate the performance of the stochastic optimization over traditional macroscopic-based optimization. In addition, this exercise can verify whether optimizing Group 2 and/or Group 3 variables can further improve the efficiency of traffic signal control.

As shown in Table 8, the GA-based optimization method produced statistically better timing plans than SYNCHRO (see the first and fourth rows). For Group 2 and Group 3 variables, the GA-based stochastic method was chosen because it showed the best performance during Group 1 variables optimizations. In addition to two do-nothing cases (i.e., cases where only Group 1 variables were optimized and Group 2 and Group 3 variables were set on the basis of engineering knowledge and a few recommended guidelines) (*22*,*23*,*24*), four more evaluation scenarios (see Table 8) were developed and optimizations were conducted for these four scenarios.

Table 8. CORSIM Evaluation Results Using V1NA, V2NA and V3NA Networks

Type of Optimization	Control Delay of V1NA (STD), seconds per vehicle [Light Traffic]	Control Delay of V2NA (STD), seconds per vehicle [Heavy Left-Turn Traffic]	Control Delay of V3NA (STD), seconds per vehicle [Heavy Traffic]
Group 1 by SYNCHRO only	12.50 (0.38)	40.05 (2.79)	73.51 (4.73)
Group 1 by SYNCHRO and Group 2 by GA	12.19 (0.33)	36.55 (2.51)	67.81 (4.46)
Group 1 by SYNCHRO and Group 3 by GA	12.71 (0.39)	41.20 (3.43)	67.24 (3.70)
Group 1 by GA only	11.51 (0.34)	28.91 (2.33)	54.45 (3.65)
Group 1 by GA and Group 2 by GA	11.32 (0.44)	27.54 (2.45)	49.12 (2.29)
Group 1 by GA and Group 3 by GA	11.79 (0.40)	29.90 (2.20)	53.77 (2.86)

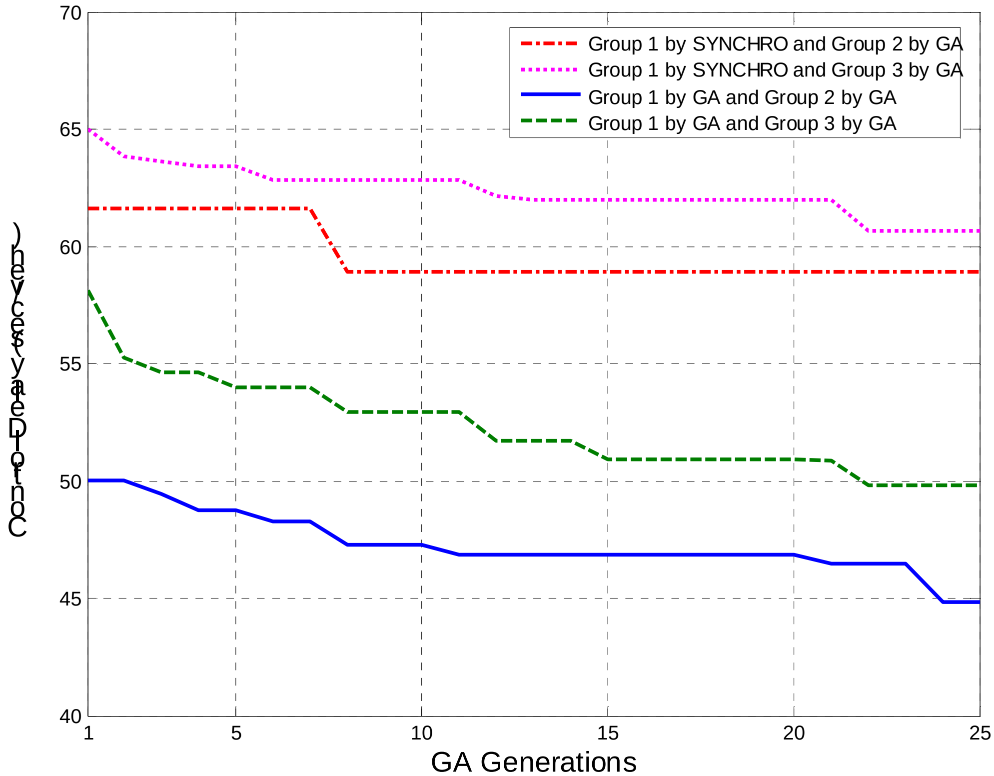


Figure 4. Convergences of Group 2 and 3 Variables Optimizations in V3NA Network (Heavy Traffic Condition)

Figure 4 shows the convergence of each optimization scenario applied to the V3NA network (i.e., heavy traffic condition). It is clear that Group 2 variables optimizations converge to lower control delays than Group 3 variables optimizations (see the top two curves where Group 1 variables were optimized by SYNCHRO; and the bottom two curves where Group 1 variables were optimized by the GA-based method). The findings were similar to the other two volume levels. These results indicate that Group 2 variables are more important than those of Group 3 in the operations of coordinated actuated signal systems.

As shown in the second column in Table 8, the improvements by optimizing Group 2 and Group 3 variables for light traffic conditions are not significant. However, the effects of optimizing Group 2 and Group 3 variables in heavy traffic conditions (i.e., congested networks) become substantial as shown in the third and fourth columns in Table 8. Especially, “Group 1 by GA and Group 2 by GA” showed significant improvement over “Group 1 by GA only.” Based on this experiment it can be concluded that there is great potential to further improve the efficiency of the coordinated actuated signal systems by optimizing Group 2 variables in congested networks. However, no significant improvements were made by optimizing Group 3 variables.

CONCLUSIONS AND RECOMMENDATIONS

This study proposed a stochastic optimization approach by combining a stochastic optimization engine and microscopic simulation model CORSIM. The proposed approach optimizes controller and detector settings in addition to four basic parameters (i.e., cycle, green split, offset and phase sequence).

Based on the stochastic optimization and simulation results using two networks with three different volume levels, the following conclusions were made:

1) Optimization capability of the five optimization methods regarding Group 1 variables:

- Stochastic optimization methods outperformed traditional optimization methods.
- Optimization of phasing sequence can significantly improve the performance of coordinated actuated signal systems.
- Among the stochastic optimization methods, the GA-based optimization method produced the best results for the networks used and volume levels considered.
- One downside of the stochastic optimization methods was the lengthy computation time requirement due to the use of the microscopic simulation model.

2) Effects of the optimization of Group 2 and Group 3 variables:

- Significant benefits were found for Group 2 variables optimization, especially in congested networks.
- The operational improvements made by optimizing Group 2 variables were relatively small.
- Group 3 variables did not improve the performance of the signal system when compared to the do nothing case.

The following recommendations were made for future research:

- Since this study used postulated networks, the CORSIM model could not be calibrated and validated. However, it is assumed that CORSIM represents "true real world field conditions." This is critical because a microscopic simulation model (whether CORSIM or others) should reflect well true field conditions such that the optimized traffic signal timing plan can work in the field. Thus, it is recommended that traffic simulation model needs (to be used in the stochastic optimization) be well calibrated and validated.
- The traffic signal control logics embedded in the microscopic simulation programs are most outdated when they were compared to actual modern traffic controllers. Thus, the use of stochastic optimization or any other approaches should be considered under the hardware-in-the-loop simulation (HILS) and/or software-in-the-loop simulation (SILS) (*27,28*). This would ensure adequate evaluations of the advanced features or new control logics of traffic controllers during the optimization.

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