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APPLICATION OF STOCHASTIC OPTIMIZATION METHOD FOR AN URBAN CORRIDOR

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ABSTRACT

This paper presents a stochastic traffic signal optimization method that consists of the CORSIM microscopic traffic simulation model and a heuristic optimizer. For the heuristic optimizer, the performance of three widely used optimization methods (i.e., genetic algorithm, simulated annealing and OptQuest Engine) was compared using a real world test corridor with 12 signalized intersections in Fairfax, Virginia, USA. The performance of the proposed stochastic optimization method was compared with an existing signal timing optimization program, SYNCHRO, under microscopic simulation environment. The results indicated that the genetic algorithm-based optimization method outperforms the SYNCHRO program as well as the other stochastic optimization methods in the optimization of traffic signal timings for the test corridor.

1 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 timing optimization has been recognized as one of the most cost-effective methods for improving accessibility and mobility at signalized urban transportation networks.

Urban transportation networks provide services to various transport modes including many types of motorized vehicles and non-motorized modes such as bikes and walks. Stochastic nature of drivers' characteristics on responses to traffic control as well as interactions with adjacent vehicles make the efforts of modeling of urban transport. As such, traditional traffic signal timing plan optimization approaches were based on macroscopic and deterministic models.

Example of these macroscopic and deterministic model-based traffic signal timing plan optimization programs includes SYNCHRO (Husch and Albeck 2004), TRANSYT-7F (Hale 2005), and PASSER™ V-03 (Texas Transportation Institute 2002). 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 (Park et al. 2001). As such, recent version of TRANSYT-7F (T7F) introduced "direct CORSIM optimization," which consists of a genetic algorithm (GA) and a microscopic traffic simulation program CORSIM to overcome those demerits of the macroscopic and deterministic optimization models. However, it is unable to optimize phase sequences and any additional signal control parameters such as extension time, minimum green time, and detector settings (Hale 2005). Foy et al. (1992) introduced a GA in the determination of signal timing for a two phase system in 1992. Hadi and Wallace (1993) 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 potential in optimizing signal timing and phasing. Rouphail et al. (2000) developed a direct signal timing optimization strategy by linking a GA and CORSIM for a pre-timed traffic signal network and compared its performance with T7F. Park et al. (2001) developed a stochastic signal optimization method using a GA interfaced with CORSIM to optimize cycle length, green splits, and offsets simultaneously for a pre-timed traffic signal system. Park and Schneeberger (2003) 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. Recently, the authors of this paper, Park and Yun (2006) developed three stochastic optimization methods via linking CORSIM with three heuristic optimization methods, including a GA, simulated annealing (SA) and OptQuest Engine, using simple theoretical networks and showed the potential of the methods in the coordinated actuated signal systems. Given the successful applications of this previous work conducted by the authors of this paper, this paper aims at applying various stochastic optimization methods to an actual large-scale signalized corridor operating under coordinated actuated signal control mode.

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

2 METHODOLOGY

This section firstly covers the selection of an adequate microscopic simulation model as well as suitable optimization methods, and then discusses the development of stochastic optimization methods used in this study.

2.1 Microscopic Simulation Model Selection

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 (2003) compared various microscopic traffic simulation models, including PARAMICS, VISSIM, CORSIM and SIMTRAFFIC in terms of computation time and capability of modeling a coordinated actuated signal control system. CORSIM was the fastest in simulation run time and it is equipped with a 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 APIs for actuated signal control systems in the United States (Park and Yun 2003). SIMTRAFFIC was computationally most expensive among these models.

2.2 Heuristic 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 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, SA and a commercial optimization program OptQuest Engine were chosen. Brief descriptions of these methods are presented in this section.

2.2.1 Genetic Algorithm

The GA was developed by John Holland in the early 1970s at the University of Michigan (Holland 1975). The GA makes up a family of computational models inspired by evolution (Whitley 1994). 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 (Holland 1975, Davis 1991, Goldberg 1989). The 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 (Houck 1995). 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 (1975). The 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 (Michalewicz 1994).

2.2.2 Simulated Annealing

Simulated annealing (SA) was first introduced by Metropolis et al. (1953). 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 the minimum energy (Carson and Maria 1997). The application of SA for deterministic optimization problems was introduced by Kirkpatrick et al. (1983). As an analogy of the annealing process for a thermodynamic system, SA firstly determines an initial energy level at initial high temperature. By perturbing the initial set of optimization variables for the system at a constant temperature, SA keeps computing the change in energy. 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, which becomes smaller as temperature decreases according to 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 increase the objective value as well as a search point that decrease it. Generally, the escape from local minima in SA is dependent on the annealing schedule, the choice of initial temperature, and the number of perturbation at each temperature, and the amount of temperature reduction (Venkataraman 2001).

2.2.3 OptQuest Engine

OptQuest Engine is commercial optimization software developed by Fred Glover in OptTek Systems Inc. (Opttek Systems Inc. 2000). 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 noisy model (Glover et al. 2006). 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 (Glover et al. 2006). OptQuest®, a software version of OptQuest engine, has been embedded in several commercial programs or simulation software such as CrystalBall (Opttek Systems Inc. 2000), and Arena (Rockwell Automation 2004), as an optimization module.

2.3 Development of Stochastic Optimization Methods

Three heuristic optimization methods for signal timing optimization were developed based on a GA and SA using the MATLAB program and OptQuest using the Visual C++.Net program. This section presents the development of the heuristic optimization. Figure 1 shows the conceptual framework for the proposed method. As illustrated in Figure 1, the stochastic signal control settings optimization method works as follows:

- A heuristic optimization method produces individual or a population of a set of signal control settings, according to the solution generation rule.
- An optimization-simulation interface module generates a CORSIM input file including a set of signal control sets transferred from the heuristic optimization method.
- CORSIM conducts random-seeded multiple simulation runs.
- Performance measures from the output files of the CORSIM runs are fed back to the heuristic optimization method by the optimization-simulation interface module.
- A heuristic optimization method evaluates the performance measures in an attempt to minimize pre-defined measures of effectiveness (MOE), and then generates a new set of signal control settings.
- This process continues until certain stopping criteria are met.

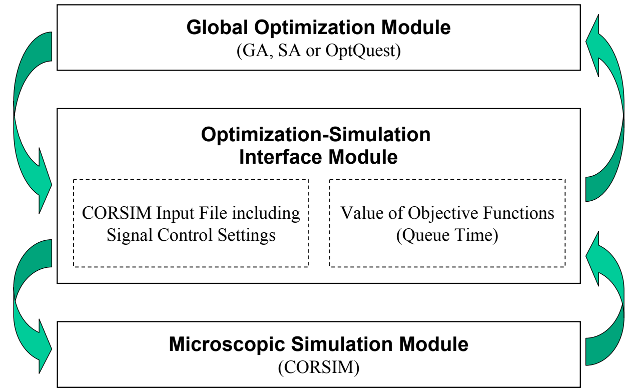

Figure 1: Conceptual Frameworks for Proposed Method (Yun 2006)

The basic signal timings (i.e., optimization variables) for a coordinated actuated signal control system are cycle length, force-off points, offsets and phase sequences: (Husch and Albeck 2004, Gordon 1996, ITT Industries Inc. 2001).

During the stochastic optimization, traffic signal timings have to meet various constraints such as minimum green time requirement, barriers, equality requirement between cycle length and the sum of green splits, etc. Thus, it is practical to adopt a decoding scheme such that optimization variables reside within feasible region during optimization. This study adopted a fraction-based decoding scheme, which was introduced by Park et al. (1999). The decoding scheme allows all of the signal timings to be feasible during the optimization. It is noted that the force off points, needed for the coordinated actuated signal control, are calculated from the cycle length, green splits and phase sequence optimized by the stochastic optimization. The same decoding scheme is applied to all three stochastic optimization methods.

In addition, it should be noted that the proposed stochastic optimization methods actually accommodate not only the basic traffic signal timings (i.e., cycle length, green splits, offsets and phase sequences), but also additional traffic signal control settings such as detector length, minimum green and vehicle extension times, which can play important roles in the efficiency of coordinated actuated signal control systems (Park and Yun 2006). In this paper, however, the signal timings to be optimized are confined to the basic signal timings in order to compare the performance of stochastic optimization methods with that of SYNCHRO, of which optimization capability is limited to the basic signal timings (Husch and Albeck 2004).

The CORSIM simulation program provides various system wide performance measures such as queue time, delay, throughput, stop time, etc (ITT Industries Inc. 2001). 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 the total queue time in vehicle-minutes (Park and Yun 2006).

3 FIELD STUDY

This section describes the test site, the data collection, the CORSIM network building, and calibration, followed by optimization results.

3.1 Site Selection and Data Collection

The test site is an urban corridor in Fairfax, Virginia, USA. The test site, presented in Figure 1, is a corridor in the Lee Jackson Memorial Highway (U.S. Route 50), including 11 coordinated actuated signals and one fully actuated signal between Sully Road and the Fairfax County Parkway. This site was chosen due to the availability of assistance from Northern Virginia Smart Traffic Signal System personnel and the ease of data collection. Real-time signal-timing plans and detector data for the 12 intersections could be extracted from the Management Information System for Transportation (MIST) workstation located in the Smart Travel Laboratory at the University of Virginia.

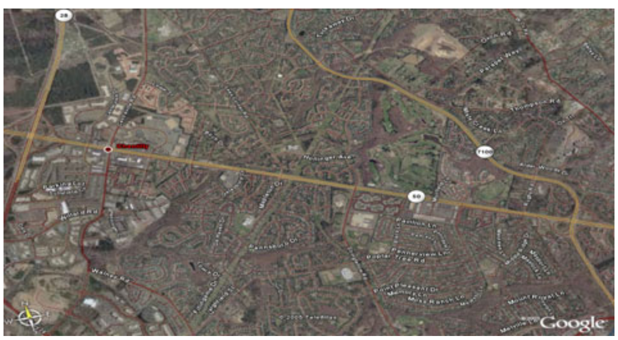

Figure 1: Test site: Lee Jackson Memorial Highway, Fairfax, Virginia (Source: <http://earth.google.com/>)

Data collection efforts were designed to provide simulation program input values and output measures of performance for calibration and validation of the CORSIM microscopic simulation program. While signal timings and link geometry attributes were provided from MIST and the Virginia Department of Transportation (VDOT), other data including traffic counts for network building, travel times, and maximum queue lengths for calibration and validation were collected directly from the site for two weekdays in 2001 (Park and Schneeberger 2003).

3.2 CORSIM Network Building

The CORSIM network for the test site was prepared in TSIS Version 5.1 by converting a SYNCHRO network, developed by VDOT, to a CORSIM network using the feature of "Transfer for CORSIM Analysis" in SYNCHRO version 6. However, the transfer feature was not perfect, so a significant amount of effort was involved in the development of comparable networks across the two programs. For fine tuning of the CORSIM network, an aerial photograph was used as a background image.

However, the lengths of cross streets on the CORSIM network are longer than those on the SYNCHRO network. In the use of microscopic traffic simulation models, it may happen that vehicles generated in a link cannot enter the network due to a long queue when the queue reaches up to the "vehicle entering point" of the link. The long queue may occur during the optimization process due to bad solutions randomly generated by the heuristic optimizer. In order to avoid such a situation, it is necessary to extend the link sufficiently to accommodate all generated vehicles from any conditions.

3.3 CORSIM Network Calibration and Validation

CORSIM includes numerous calibration parameters to be fine-tuned by the user in order to replicate observed field traffic conditions (ITT Industries Inc. 2001). Among these parameters, the driver behavior parameters were calibrated to match the field traffic conditions. The total of 14 calibration parameters was selected after careful reviews of the CORSIM manual and related references (ITT Industries Inc. 2001, Park and Qi 2005, Park et al. 2006).

Previously proposed microscopic simulation model calibration and validation procedure by Park and Qi (2005) and Park et al. (2006) was applied to this CORSIM network. The calibration and validation procedure followed in this paper is briefly provided below. Readers who wanted to access to the entire procedure should refer to Park and Qi (2005) and Park et al. (2006).

- Simulation model setup
- Initial evaluation
- Feasibility test using Latin Hyper-cube design
- Parameter calibration using a genetic algorithm
- Evaluation of the parameter set
- Validation and visualization

As a measure of effectiveness (MOE) for calibration, the eastbound travel times experienced by vehicles using the most left lane were used. The 613.2 seconds in Figure 2 is the average travel time from the field survey. The histograms were drawn using the travel times from 100 random-seeded CORSIM simulation runs based on the default and the fine-tuned calibration parameters, found by the GA-based optimization. Figure 2 depicts the distribution of travel times among 20 bins, with centers specified by ticks on the x-axis.

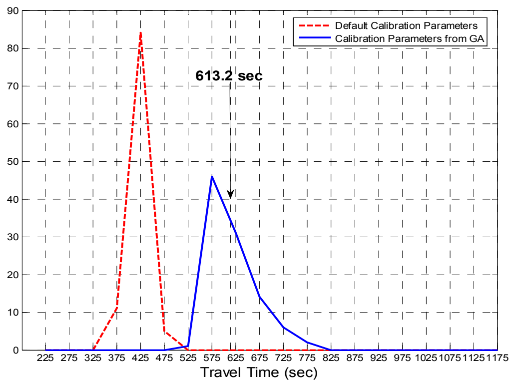

Figure 2: Histogram of Travel Times of CORSIM Networks with the Default and the Calibrated Parameters (note: Y-axis is frequency)

In order to validate the set of calibrated parameters using the GA-based optimization, the data set of maximum queue length, which has not been used in the calibration, was applied in this section. The simulated maximum queue length in the validation is very close to the actual maximum queue length as shown in Figure 3. The 24 vehicles in Figure 3 is the average value of the maximum queue lengths from the field survey. The histogram was drawn using the maximum queue lengths from the same CORSIM simulation runs used in Figure 2.

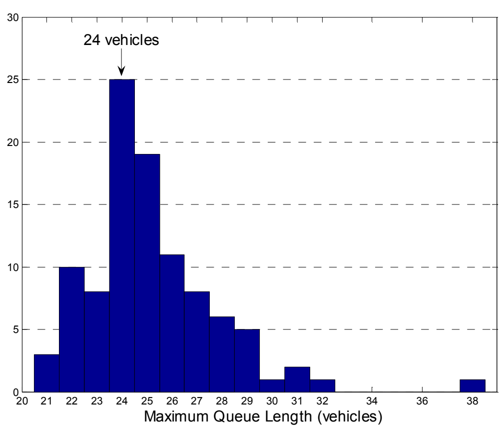

Figure 3: Maximum Queue of CORSIM Network with Calibration Parameters from GA (note: Y-axis is frequency)

3.4 Settings for Heuristic Optimization Methods

In this paper, a total of 82 signal timings including a cycle length, green splits, offsets and phase sequences were optimized. During the optimization, two other stopping criteria were used in conjunction with the maximum number of iterations (2,500): (i) lack of improvement in the fitness of the best solution after 1,000 iterations or, (ii) no difference between the fitness of best solution and the average fitness of all solutions after 1,000 iterations. A completed description of for the proposed heuristic optimization methods as well as two existing signal timing optimization programs can be found in Yun (2006).

3.5 Convergence of Stochastic Optimization Methods

The convergence properties of all the three stochastic optimization methods are graphically presented in Figure 4 by illustrating the best value of queue time in vehicle-minutes in each iteration. As shown in Figure 4, the SA-based and the OptQuest-based methods ended at the 1642nd and the 1800th iterations, respectively, due to no improvement in the queue time of its best solution while the GA-based method was terminated at the maximum generation number.

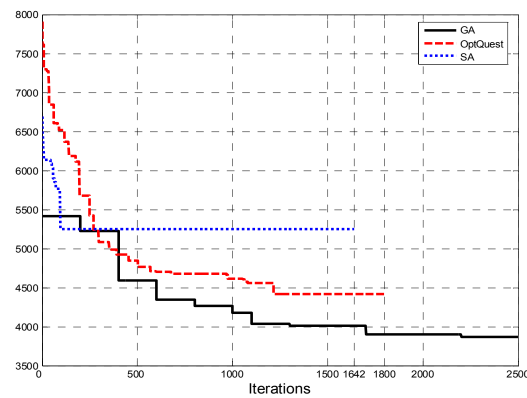

Figure 4: Convergence of Three Stochastic Optimization Methods (note: Y-axis is total queue time in vehicle-minutes)

3.6 Comparison of Performance

Performance of the existing signal timing optimization program, SYNCHRO, and three stochastic optimization methods developed in this paper was compared in Table 1 with the average values of control delay in seconds per vehicles and queue times in vehicle-minutes from 100 random-seeded CORSIM simulation runs. It is noted that the base case in Table 1 indicates the existing traffic conditions prior to applying SYNCHRO and the three stochastic optimization methods. The queue time was used in optimization process as an objective function and the control delay was added because it is known as the most important and easiest MOE to measure the level of service of a signal system.

In Table 1, SYNCHRO showed 13.3% reduction in queue time when it was compared with the Base Case. The GA-based method indicated 31.2% reduction in the same MOE whereas the OptQuest and the SA-based methods produced 15.0% and 11.5% reductions, respectively.

Like the previous study (Park and Yun 2006), the GA-based method showed the best performance. However, SYNCHRO shows its limitation in considering field traffic patterns during the optimization process because it is based on macroscopic equations, to calculate MOEs related to optimization. The OptQuest-based method produced a similar performance to SYNCHRO. The SA-based method produced worse performances unlike the previous study (Park and Yun 2006). This may be because the parameter settings for the SA-based optimization were determined via a sensitivity analysis based on the test network used in the previous study, and then the settings were applied to this study without any changes. In addition, the number of signal timing optimized in this paper is larger than the one in the previous study. Therefore, it can be concluded that the SA-based optimization is sensitive to the parameter settings for optimization and the number of signal timings to be optimized, unlike the GA-based optimization method.

Table 1. Comparison of Optimization Results

Type of Optimization	Control Delay (Average/Standard deviation), seconds per vehicle	Queue Times (Average/Standard deviation), vehicle-minutes
Base Case	23.11 / 0.63	6,014.05 / 181.68
SYNCHRO	20.23 / 1.11	5,215.26 / 281.93
GA	**17.21 / 1.16**	**4,138.36 / 325.83**
SA	22.68 / 1.14	5,321.50 / 372.43
OptQuest	20.98 / 2.01	5,114.15 / 658.20

4 CONCLUSIONS AND RECOMMENDATIONS

This paper presented an application of stochastic optimization method for a large-scale signalized corridor. The development of the proposed stochastic optimization methods was conducted via linking the CORSIM microscopic traffic simulation model with one of heuristic optimization methods including GA, SA, and OptQuest. The main feature of the proposed stochastic optimization method is the ability to optimize signal timings in a more realistic microscopic simulation environment by taking account of the stochastic variability common in a transportation system.

The results of analyses in this study indicated that the GA-based optimization method consistently outperformed SYNCHRO and other methods including the OptQuest-based and the SA-based optimization methods. The signal timings optimized by the GA-based method consistently reduced both control delay and queue time in those average values as shown in Table 1.

Even though this application is successful, there is a need for further research effort in the application of the GA-based optimization method. First, it was found that the stochastic optimization method may be sensitive to the parameter settings for optimization and the number of signal timings to be optimized. Therefore, the transferability of the stochastic optimization method in terms of the parameter settings for optimization and the number of signal timings, which is proportional to the size of the network under examination, should be dealt in a systematic way. A significant demerit of the stochastic optimization method is huge computational requirement. The reduction of required computational time can be achieved by further enhancements in computer technology and parallel computing. Finally, the signal timings optimized by SYNCHRO and the stochastic optimization methods were evaluated using the calibrated CORSIM network even though the CORSIM model was already used in the optimization process. This may cause a problem of unfair comparison between SYNCHRO and other methods. Therefore, there is a need for the use of unbiased evaluation methods to validate signal timings.

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