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ASSESSMENT OF A STOCHASTIC SIGNAL OPTIMIZATION METHOD USING MICROSIMULATION

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Abstract

A stochastic signal optimization method based on a genetic algorithm (GA-SOM) that interfaces with the microscopic simulation program (CORSIM) is assessed. As an evaluation testbed we use a network in Chicago consisting of nine signalized intersections. Taking CORSIM as the best representation of reality, the performance of the GA-SOM plan sets a ceiling on how good any (fixed) signal plan can be. An important aspect of this approach is its accommodations of variability. We also discuss the robustness of an optimal plan under changes in demand. We use this benchmark to assess the best signal plan generated by TRANSYT-7F (T7F) version 8.1, from among 12 reasonable strategies. The performance of the best T7F plan falls short of the benchmark on several counts, reflecting the need to account for variability in the highly stochastic system of traffic operations, which is not possible under the deterministic conditions intrinsic to T7F. As a sidelight we also compute the performance of the GA-SOM plan within T7F and find that it performs nearly as well as the optimum T7F plan.

Introduction and Background

Among the many tools available to the transportation engineer to deal with the thorny issue of urban traffic congestion, improved traffic signal timing has always stood out as a very cost-effective approach. Presently, signal timing plans in the U.S. are for the most part generated from a variety of deterministic, macroscopic optimization programs. Examples include TRANSYT-7F (*1*), PASSER-II (*2*), and SYNCHRO (*3*). The advantages of using macroscopic models are computational speed and simple input data requirements. However, these models cannot realistically represent the very complex characteristics of urban traffic networks including the variability in drivers' behavior, the effect of mixed traffic modes, the impact of parking and bus flows, and of course the randomness in arrival patterns. As a result, signal-timing plans that are derived from macroscopic models might not respond well to real-world traffic conditions. The authors' recent study on the reliability of TRANSYT-7F (T7F) optimization schemes indicates that discrepancies do exist between macroscopic and microscopic simulation results (*4*).

Further, the authors have demonstrated that a direct signal optimization using Latin Hypercube Design (LHD) search (*5*) produced superior timing plans to T7F when those signal plans were evaluated in CORSIM (*6*). The LHD based search was limited to offset optimization, but could be extended to include cycle length and splits. In (*6*) the cycle length and green splits were taken from T7F. Later, the authors developed a stochastic signal optimization method using a genetic algorithm (GA-SOM) interfaced with the CORSIM microscopic simulation that optimizes cycle length, green splits, and offsets simultaneously for a signalized network (*7*).

The use of CORSIM as an assessment or evaluation platform is grounded in its general acceptance and, in a recent study (*8*) that shows its capability to reflect reality and inherent traffic stochasticity. Because CORSIM is stochastic, performance measures must be assessed through multiple runs and summarized in distributions and other reflections of variability. With fixed ‘expected’ demand volume on the network multiple CORSIM runs can simulate the effect of day-to-day variations in arrival patterns, turning percentages, driver characteristics, etc. But, it cannot cope with significant demand changes while maintaining the same expected or average demand volumes. To assess the effect of variability in the ***expected*** demand we vary the input parameters (demands) at random (to reflect uncertainty about what the right expected values might be). In addition, we assess the effect of a uniform increase in demand conditions to evaluate the performance of an “aging” control plan subject to demand increase.

Since GA-SOM is the optimum choice under a performance measure within CORSIM it cannot be improved. Its performance sets a ceiling and a benchmark to which other plans can be compared. A strategy that produces plans nearly as effective and much easier to obtain would be a desirable one. What we see below, for example, is that T7F plans are not inherently able to deal with variability and this is reflected in their falling well short of the benchmarks (see Table 1). Interestingly, the reverse situation, assessing GA-SOM within T7F (see Table 2), shows that the GA-SOM measures up to T7F standards. By itself, this is not particularly meaningful, since the environment of T7F cannot capture the variability in the field that must ultimately serve as the arena for evaluation; but it does raise questions whether deterministic methods such as T7F are useful at all.

The paper is organized as follows. The **network and evaluation** section presents the CORSIM network and the approaches we take are in the **methodology** section. In **Comparison of signal timing plans** we compare the performance of T7F and GA-SOM plan in CORSIM and, as a sidelight, we compare the plans within T7F as well. The following two sections deal with performance under changes in demand. A **discussion** section is followed by **conclusions and recommendations.**

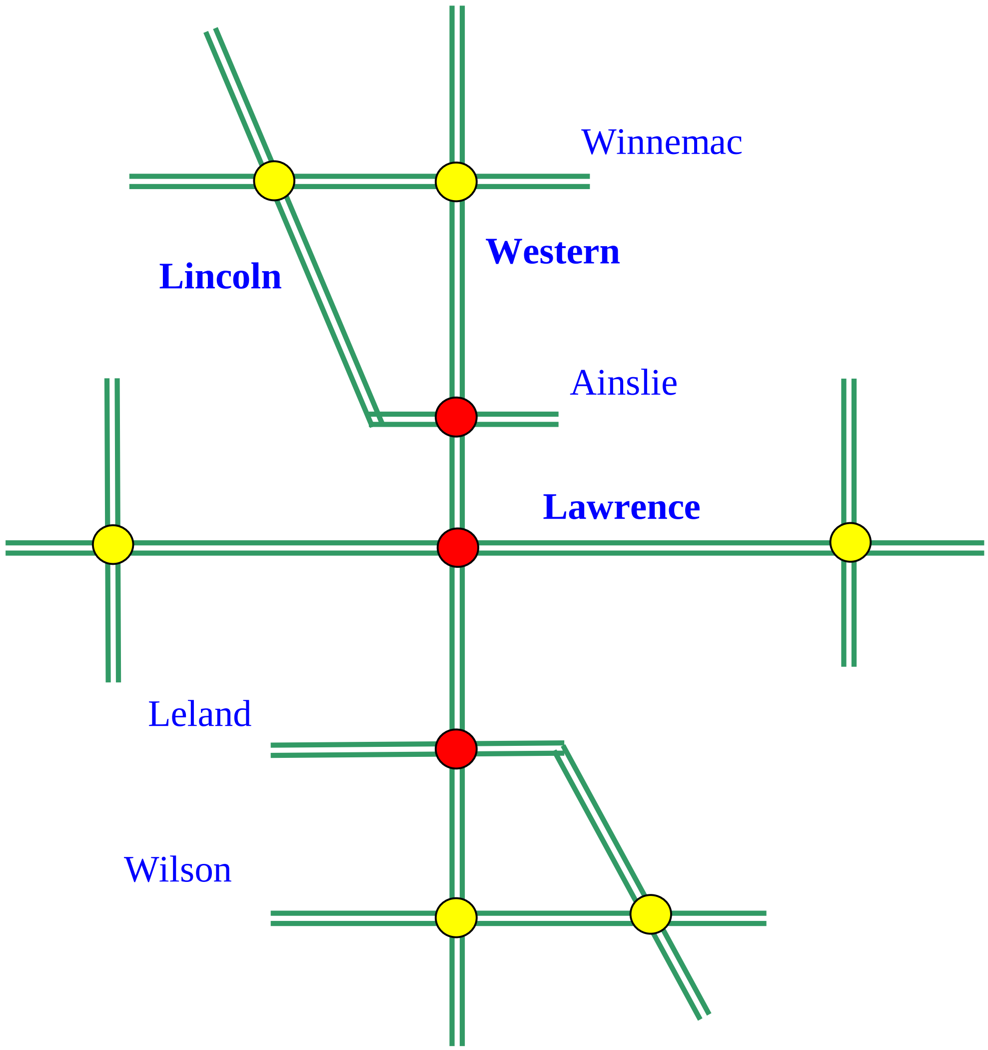
Test Network and Evaluation

The test network in Chicago consists of nine signalized intersections, and is coded in CORSIM with 59 links, and 31 internal nodes as shown in Figure 1. Traffic volume data were collected on a representative weekday for both AM and PM periods. Vehicle arrivals (cars, trucks, and buses) were manually collected at each entry node for the entire period. Turning movements were also collected: some for a short period (15 minutes), some for one hour. The maximum queue lengths (MQL) at key intersection approaches were also collected for evaluation purposes. The queue lengths are recorded every cycle over the hour and the maximum value is taken as the MQL. The selection of MQL as an evaluation criterion rather than, say, delay, was on the basis of cost and ease of collection.

The network was coded in both T7F (version 8.2) and CORSIM (release 4.2) formats. Every effort was made to develop compatible T7F and CORSIM networks. For example, queue discharge headways in CORSIM inputs were matched with saturation flow rates in T7F, so were the selections of free flow speeds and speed limits.

To assess the ability of CORSIM to reflect reality we had previously (*4*) compared the MQLs from the field with a distribution of MQLs obtained from 100 CORSIM simulation runs. The field values were consistent with the CORSIM generated values.

Figure 1. Test Network (Chicago, IL)



Methodology

TRANSYT-7F

T7F is a widely used urban traffic signal optimization package. Its most recent U.S. release (version 8.2) contains desirable features such as explicit modeling of saturated and queue spillback conditions, step-wise simulation, horizontal queuing, multiple cycles and multiple periods, and optimization under congested conditions (*1*). It is considered by many as representing the state of the practice in signal optimization. T7F can optimize delay, fuel consumption, stops, throughput, progression opportunities (PROS), and multiple combinations of these. In a previous study (*4*) the authors tested twelve possible signal optimization strategies in T7F and determined $PROS^2/DI$ as the best strategy in T7F itself. The authors also evaluated those in CORSIM and determined that the best strategy for queue time minimization on the test network in Figure 1 is PROS/DI.

CORSIM

CORSIM is a stochastic and periodic-scan based microscopic simulation program of urban traffic developed for FHWA (*9*). Two basic link statistics generated in CORSIM are delay and queue time. Individual vehicle delay is calculated as the time difference between the actual and free-flow link travel time for a driver-vehicle unit. The average link delay is obtained by dividing the total delay time (experienced by vehicles that have already traversed the link) by the number of vehicles that have discharged from the link. Queue time is the time accumulated in a queue that is caused by the link control. Previous work indicated that CORSIM may underestimate the actual delay reported under "congested" conditions because the delay in CORSIM excludes that accrued by vehicles that remain on the network at the end of a simulation run (*10*). We therefore opted to use network queue time as the performance measure.

GA-based Stochastic Optimization Method (GA-SOM)

Park *et al.* (*7*) developed a stochastic signal optimization method using a genetic algorithm that interfaces with the CORSIM microscopic simulation program. That approach is capable of optimizing signal timings in a stochastic traffic environment. The method works as follows.

First, initial signal timing plans with in binary representation form are randomly produced. A REXX (*11*) code, (a script language-based computer program) converts the timing plans into integer values and inserts them directly into a CORSIM input file.

(REXX works as an interface between CORSIM and the GA optimizer). A single CORSIM run for each tested signal plan is executed. This process continues until all signal timing plans proposed by the GA optimizer (see next paragraph) are run.

A second REXX code extracts the performance measures for each signal plan from the corresponding CORSIM text output file. These performance measures are then fed to a GA. The GA in turn evaluates the performance measures, and then generates a new set of signal timing plans. This whole routine continues until a pre-specified number of iterations is reached.

The objective function provided to the optimizer can be any combination of outputs produced by CORSIM. In our application, we minimized system queue time.

Minimize $$SQT = \sum_{i=1}^{L} QT(i)$$

where

SQT = system queue time,

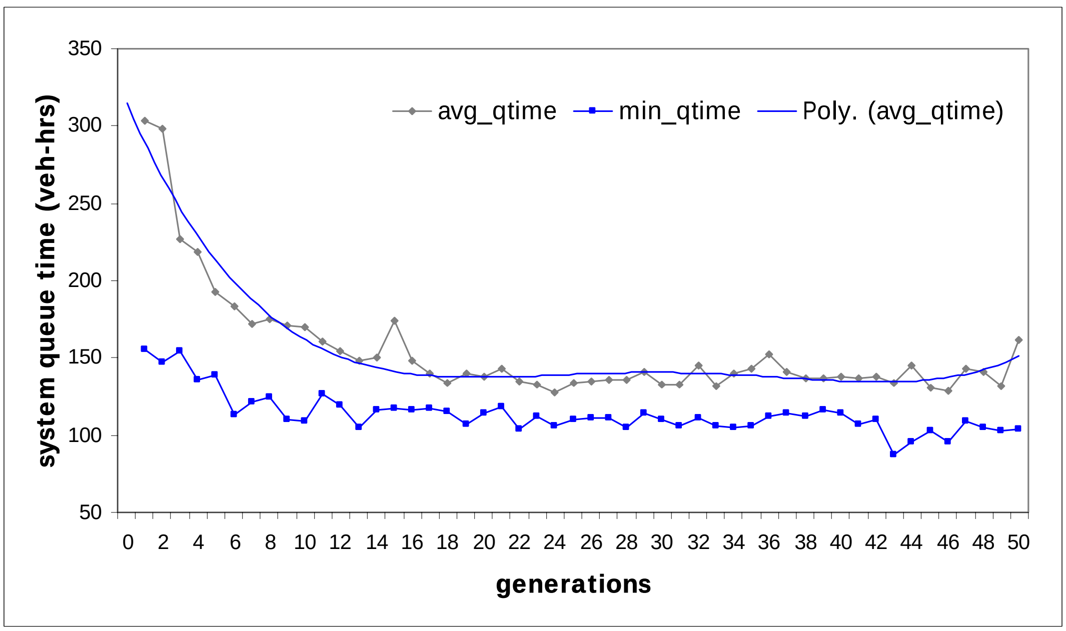
QT(i) = queue time on link i, i=1,…,L, and

L = number of one-way links on the network.

The GA-SOM can simultaneously optimize cycle length, green splits and offsets. There are several parameters that govern the behavior of a GA procedure. These include maximum number of generations, population size, crossover and mutation probabilities, etc. We used a population size of 25 and maximum number of generation of 25. We did experiment with 50 generations and found no visible benefit. Further details on the method can be found in Park *et al.* (*7*).

An important challenge in stochastic signal optimization is the ability to overcome random variability. The objective function value shown above includes random error since each observation is an output from a single CORSIM run. The convergence properties of GA-SOM are plotted in Figure 2. The minimum queue time, which is the "best" individual among 25 at each generation, stabilizes after about five generations (bottom line in Figure 2). The optimal solution is the best plan achieved at generation 25. Thus from the 5th to the 25th generations, the best solution is continuously refined. The best timing plan, which is automatically transferred to the next generation (due to the elitist method in GA) is reevaluated in CORSIM with different random number seeds. Therefore, a signal plan that tends to produce less variability as well as less queue time is more likely to survive to the next generation. After 18 generations, the average queue time (i.e., an average of all individuals) becomes stable (top line in Figure 2) indicating that GA-SOM is converging.

Figure 2. Convergence properties of GA-SOM



Comparison of Signal Timing Plans

In this section, GA-SOM and the best T7F timing plans are evaluated on the basis of both CORSIM and T7F.

Results of the 100 CORSIM simulation runs for GA-SOM and T7F are summarized in Table 1. The comparisons are striking: as shown in Figure 3, the histograms for the GA-SOM plans lie substantially to the left of those of the T7F and are far less variable.

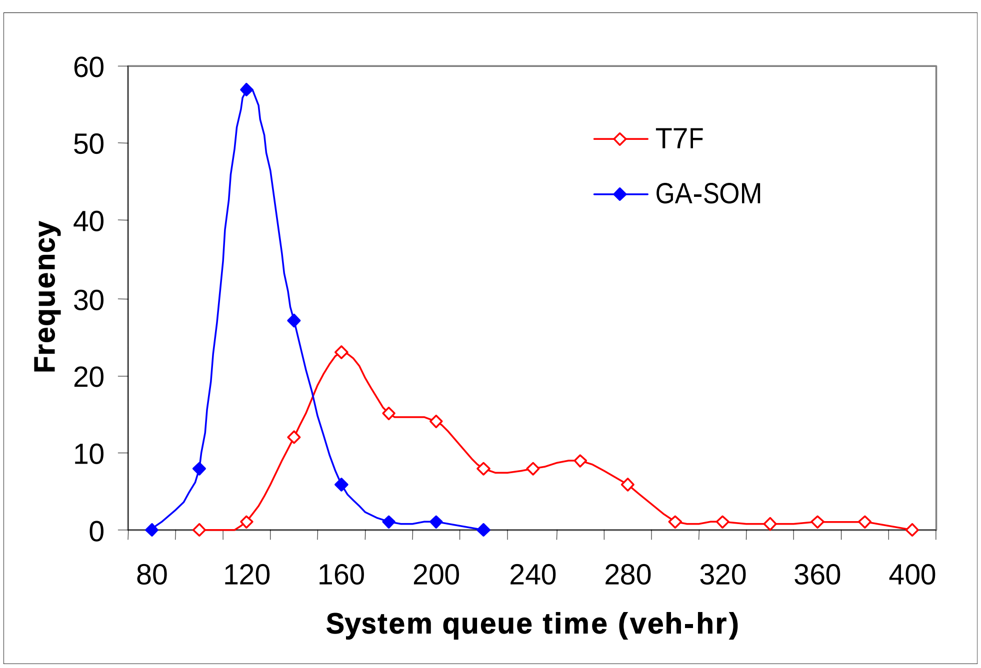
Potentially alarming is the long tail in the distributions for T7F – high values (say above 300 veh-hrs) are indicative of serious spill-back, even gridlock. On the basis of these numbers it is clear that T7F is a less desirable plan.

Table 1. Comparison of GA-SOM and T7F in CORSIM

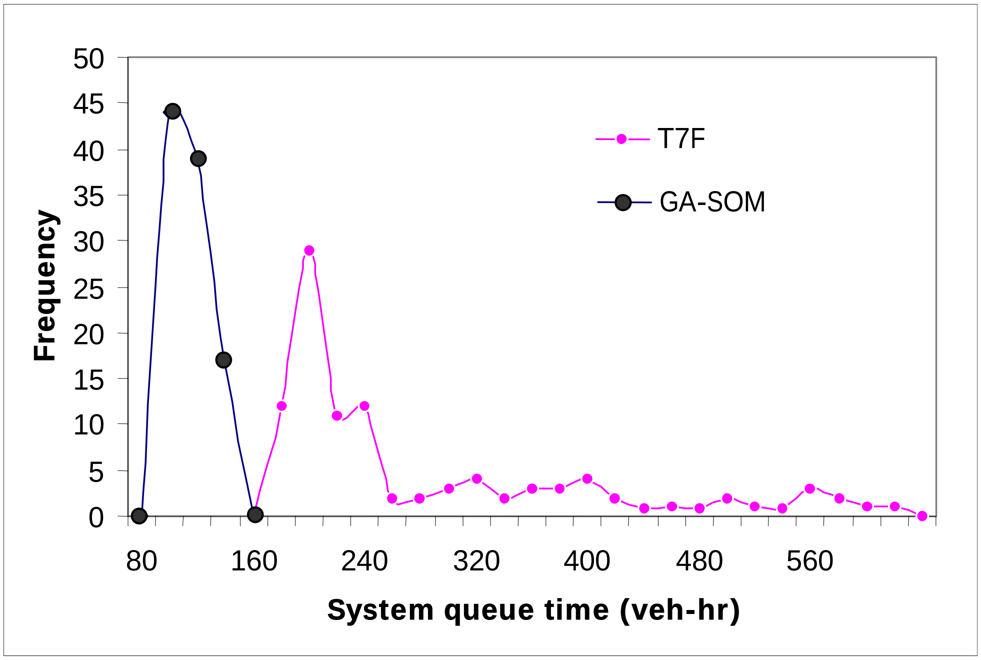
Time Period	Signal Plan	Cycle (sec)	Delay (sec/veh)	Queue Time (veh-hrs)	Throughput (veh)
			Avg/Median/SD	Avg/Median/SD	Avg/Median/SD
AM Peak	T7F	65	21.5/19.8/5.0	184.7/167.0/51.7	40876/41207/1107
	GA-SOM	70	15.6/15.1/2.2	119.3/114.1/21.7	42563/42593/271
PM Peak	T7F	65	23.6/22.6/3.3	268.4/216.6/115.0	35900/40099/7214
	GA-SOM	70	14.4/13.9/1.8	108.3/103.6/16.7	42354/42420/369

Note: T7F: Best TRANSYT-7F strategy (PROS/DI)
GA-SOM: Stochastic optimization method (queue time minimization strategy)
Medians are reported to allow comparisons minimally affected by outlier observations

Figure 3. Performance of T7F and GA-SOM: Histogram based on 100 CORSIM runs



(a) AM period



(b) PM period

To explore the effect of using the T7F platform, we fed the GA-SOM and the best T7F plans (as mentioned in the previous section) into the T7F simulator and compared their performances. The performance of a T7F plan in the T7F simulator differed from the output at the end of the optimization. This is due to the initialization required in T7F's step-wise simulation. We decided to use the T7F performance from the simulation output, to be consistent with the performance of the GA-SOM plan in the T7F platform. The comparisons are in Table 2. Not surprisingly, T7F is better. But the difference are marginal and clearly outweighed by the disparities in Table 1, which represents more closely performance expected in the field.

Table 2. Comparison of GA-SOM and T7F in T7F

Period	Signal Plan	Cycle (sec)	Average Delay (sec/veh)	Total Travel Time (veh-hr/hr)	Stops (%)
AM Peak	T7F	65	22.0	306	79
	GA-SOM	70	24.5	326	79
PM Peak	T7F	65	33.4	414	85
	GA-SOM	70	39.2	460	84

Note: T7F: Best TRANSYT-7F strategy (PROS^2/DI) chosen from T7F itself.
GA-SOM: Stochastic optimization method (queue time minimization strategy)

Random Changes in Demand

Even though the 100 CORSIM simulations can adequately simulate the day-to-day variations in traffic patterns and driver behavior, the mean number of arrivals at the external nodes remains constant. In reality, these mean arrival inputs will themselves change over time. Moreover, the estimates of these mean rates are based on traffic counts collected by manual observers, and are subject to considerable error. We therefore evaluated the response of the plans to changes in these mean rates.

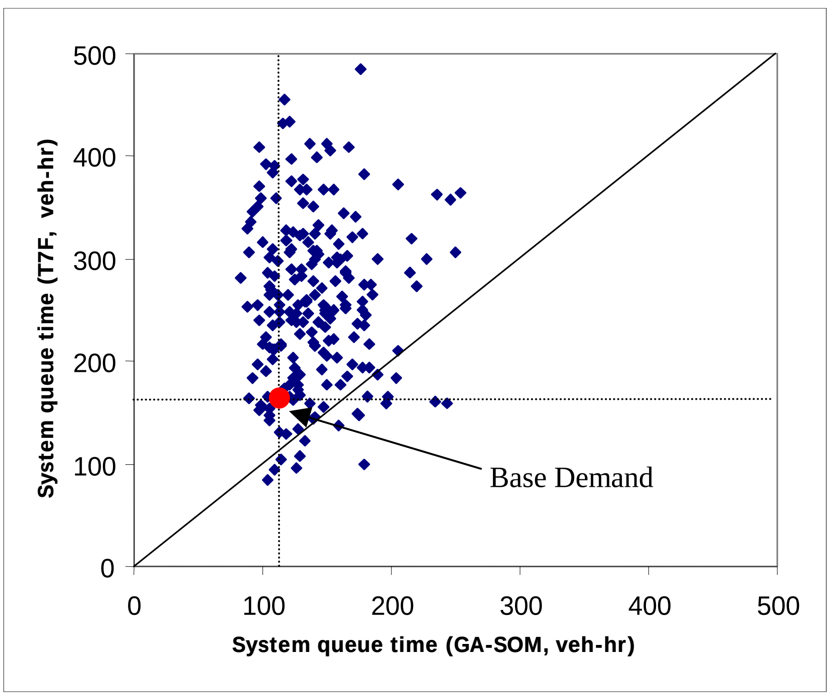
We chose a substantially wide range of changes to explore: (±15% from the base demands at each entry node). Since there are eight major external input demands, the number of possible demand patterns that can be tested is quite large (31^8) if only integer percentages are used. An efficient sampling method using a Latin Hypercube Design was applied to the problem. This is a stratified sampling technique where the input variable distributions are divided into equal probability intervals (*5*). It can be considered as a deterministic version of Monte Carlo simulation, but one that can maximally cover the design surface with near zero correlations among input parameters. A LHD requires far fewer samples than simple Monte Carlo methods (*12*). A detailed algorithm can be found in McKay *et al.* (*5*).

A total of 204 demand combinations were created from the LHD algorithm. For the AM peak, 10 simulations were made for each demand combination, resulting in 2,040

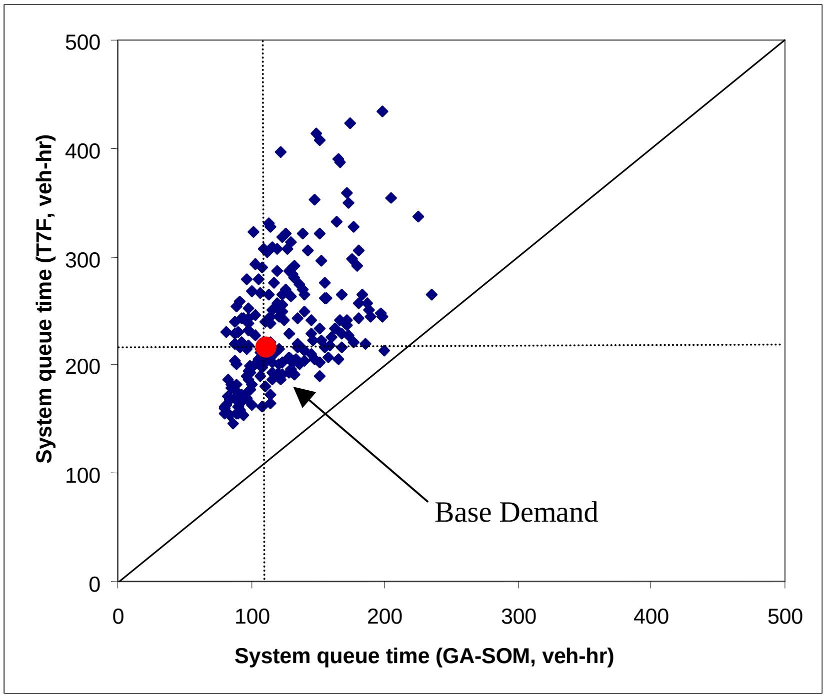
CORSIM runs. For the PM peak, only 4 simulation runs for each demand combination were made, resulting in 816 CORSIM runs. Since each peak period has two optimal timing plans, one from T7F and another from GA-SOM, a total of 2 × (2,040+816) = 5,712 CORSIM simulation runs were conducted.

Figure 4 (a) depicts the robustness of the AM signal timing plans to varying external demands. In approximately 95% or more cases, the GA-SOM plans produced less queue time than T7F. Furthermore, the range of queue times for the T7F plans is 90 to 500 vehicle-hours, while that for GA-SOM is 90 to 270 vehicle-hours. Even more dramatic results were observed for the PM timing plans. As shown in Figure 4 (b), under all demand combinations the GA-SOM plans produced less queue time than that of T7F.

Figure 4. Comparison of T7F and CORSIM under varying demand



(a) AM period (each point represents an average of 10 CORSIM simulation runs)



(b) PM period (each point represents an average of 4 CORSIM simulation runs)

Systematic Change

The determination and field implementation of optimal settings is not the end of the road for many traffic signal engineers. A nagging question is: when does the current signal plan need updating? Suppose that traffic demand on the network increases over time. One would like to update the current signal setting at the most appropriate time if possible. As an initial step we compared the degradation in system performance if the current signal settings were to be retained under a new demand pattern, or are updated to accommodate the new demand. In theory, this is the benefit derived from having an adaptive signal system such as RT-TRACS that can automatically respond to demand changes.

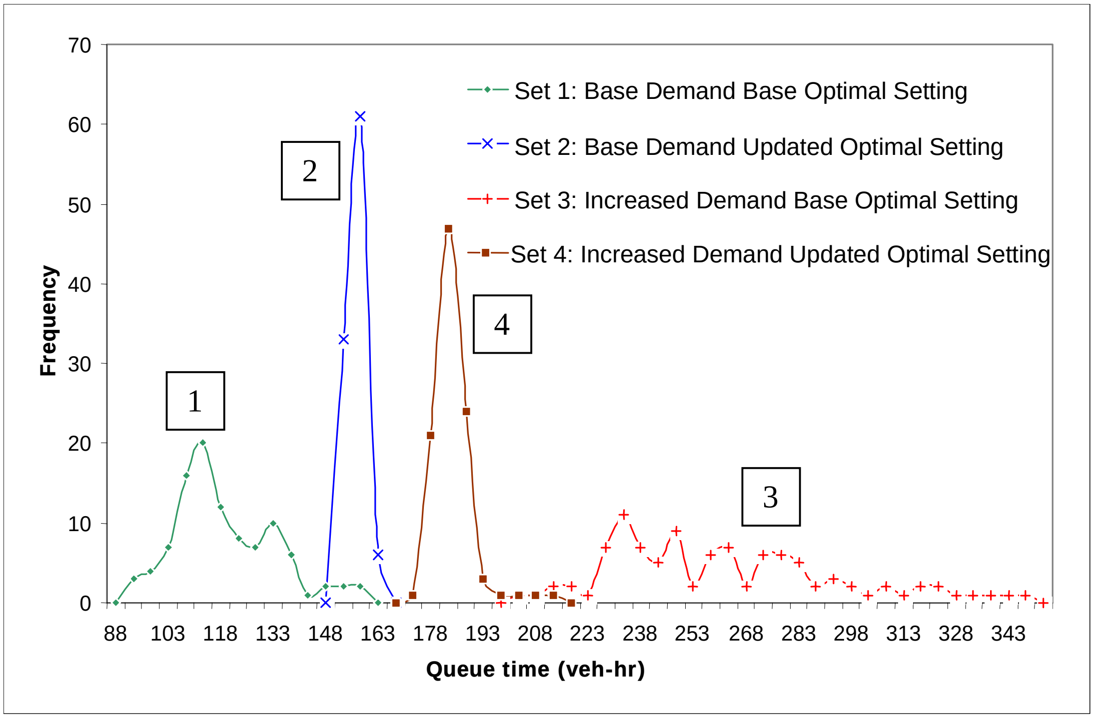
In this study, the four scenarios shown below were evaluated in CORSIM for the AM peak period using:

1. Base demand and corresponding base optimal GA-SOM signal plan.

2. Base demand and updated GA-SOM signal plan (generated from an updated demand that is 10% above the base demand).
3. Updated demand with base optimal GA-SOM signal plan.
4. Updated demand and updated GA-SOM signal plan,

Again, 100 CORSIM confirmation runs for these four sets were made and distributions of system queue time were obtained. The comparison results are shown in Figure 5. It is evident that a do-nothing approach could be very costly. For example, if demand actually increases, and no changes are made to the signal plan, then the distribution shifts from set 1 to set 3, representing a drastic degradation is system performance. If changes are made to the signal plan in response to the demand increase, then the performance still degrades, (to set 4) as expected, but far better than set 3. The truly interesting set is 2, which represents the situation where demand actually does not increase, but signal plans are generated on the basis of a 10% demand increase. Again, as expected, set 2 is worse than set 1though less variable. So, the region between sets 2 and 4 inclusive represents the expected performance of the network for demand changes that can vary from zero to 10% with signals plans based on a 10% demand increase. Similarly, the region between sets 1 and 3 inclusive represents the expected performance of the network for demand changes that can vary from zero to 10% with signals plans based on base demand. Given the choice of performance and the uncertainty in demand prediction, the results in Figure 5 strongly suggest that a good strategy is to develop signal plans with an assumption of increased demand rates, whether or not that assumption can be fully justified at this time. That is, trade off some current performance to protect against the more severe degradation that would follow an increase in demand.

Figure 5. Performance sensitivity to 10% increased demand (AM period)



Discussion

The use of microscopic traffic simulation as part of a signal plan development is very promising, even though the computational burden is non-trivial. With a Pentium II (450 MHz) computer, T7F took about 10-20 minutes to produce a single strategy while obtaining the GA-SOM took about 7-8 hours. A T7F run conducted cycle length evaluation (starting from 50 seconds to 120 seconds in every 5-second increment) with multiple cycle and step-wise simulation options, while the GA-SOM used a total of 625 (25 population size × 25 generations) CORSIM simulation runs. Nonetheless, the one-time computation of a good plan can translate into far greater benefits in the field.

The sensitivity analysis of the base and updated plans under scenarios of increased demand suggests a useful tool: design a signal plan for prospective greater demand and guard against serious degradation at the expense of a modest loss in current performance.

Moreover, if demand can be predicted within a reasonable range, then the timing of the introduction of new plans can be factored into overall traffic management and operations.

CONCLUSIONS AND RECOMMENDATIONS

This work began with the premise that signal plans that are derived using a high fidelity, properly validated traffic model will yield optimal traffic performance. The CORSIM model has the ability to represent the stochastic urban traffic environment in great detail. It has a history of acceptance by transportation professionals, and elements of it have been validated over time (as was done in this study). Thus, the GA-SOM signal plans derived from CORSIM were expected to provide solid performance in the simulator. Those expectations were met, at least for our test network. Additional testing is essential if we are to trust our initial observations. In fact, another network in Chicago, three times the size of our test network, was re-timed in September 2000 using GA-SOM and initial field results confirm the improvements predicted through CORSIM (*13*).

By contrast, the signal plans derived from T7F were significantly less effective. Strikingly, GA-SOM produced much less variation in system performance compared to T7F settings, particularly under varying demand conditions.

The computational demands for implementation of the GA-SOM approach are outweighed by the approach's explicit accounting for the stochastic nature of traffic flow in the development of signal plans. And, since the needed computations are suitable for parallel computation, even this barrier can be largely overcome.

Based on our findings, the following recommendations are made: First, the variability of system performance associated with a signal plan should always be considered in evaluating the traffic performance of that plan. Second, further confirmation should be sought on the value of a signal setting obtained assuming higher than base demand levels: is such a tactic good enough for base demand and more resistant, than a base optimal plan, to degradation in performance under increased demand? Third, and perhaps most important of all, is that direct optimization and comparison should be done within a platform that adequately captures the realities in the field.

Acknowledgements

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