OPTIMIZING SIGNAL TIMINGS TO IMPROVE SAFETY OF SIGNALIZED ARTERIALS

Aleksandar Stevanovic
Assistant Professor of Civil Engineering, Florida Atlantic University,
Boca Raton FL, USA, e-mail: astevano@fau.edu.

Jelka Stevanovic, PhD
Independent consultant,
Boca Raton FL, USA, e-mail: jelkastev@yahoo.com.

Cameron Kergaye
Director of Research, Utah Department of Transportation,
Salt Lake City UT, USA, e-mail: ckergaye@utah.gov.

Submitted to the 3rd International Conference on Road Safety and Simulation,
September 14-16, 2011, Indianapolis, USA

ABSTRACT

One way to improve safety of signalized arterials is to optimize signal timings. Historically, signal retiming tools were used to reduce traffic delay and stops and other measures of traffic efficiency. The concept of optimizing signal timings specifically to improve safety metrics, or their surrogate measures, is not common in current signal timing optimization practice. This study advocates a fresh approach to integrating VISSIM microsimulation software, SSAM, and VISGAOST for optimizing signal timings to reduce surrogate safety measures and thereby reduce risks of potential real-world crashes. In addition, a multiple-objective genetic algorithm is implemented into VISGAOST to identify the optimal compromise between two competing objectives: surrogate safety and traffic efficiency. A 12-intersection corridor on Glades Road in Boca Raton served as a case study. Optimized signal timings delivered a solution that balanced both safety and efficiency. When compared to initial signal timings the estimated number of conflicts was reduced by 7%. In addition, when compared to signal timings optimized for efficiency the estimated number of conflicts was reduced by 9% without a significant loss of efficiency (~1%). The study also approximated a Pareto Front of conflicts and throughput which may be instrumental when trading off (surrogate) safety for efficiency in the development of signal timing plans. Further research is needed to test the approach on a variety of networks and traffic conditions and to find a good composite measure for single-objective optimizations.

Keywords: traffic signals, surrogate safety measures, multi-objective optimization, evolutionary algorithms, simulation.

INTRODUCTION

One way to improve safety of signalized arterials is to retime traffic signals. Well-coordinated traffic signals provide good progression for major vehicular streams thus reducing the number of necessary stops and the potential for rear-end collisions. Also, balanced splits provide more equitable green times for all traffic movements thus reducing potential for unsafe operations of 'unfairly treated' traffic movements. However, in spite of the common understanding that proper signal timings promote safe traffic operations, there is little evidence from the field to support this understanding. The Highway Safety Manual (HSM, 2010) states that several signal timing-related crash-reduction treatments (e.g. modifying cycle length and phase durations and improving signal coordination) have unknown effects on crashes.

Two major reasons account for an inability to investigate impacts of signal timings on traffic safety at intersections on arterial streets. First, field evaluations of safety improvements obtained by tweaking signal timings are impractical and often inconclusive. Relationships between crash rates and potential causes are relatively low even when those causes (e.g. weather, geometrical design of the roads, and presence of work zones) have much higher impact on traffic safety than signal controllers' timings. Second, unlike other traffic metrics which reflect efficiency of traffic operations, safety impacts have not been traditionally assessed in simulation tools.

Recent research (Gettman and Head, 2003) on use of surrogate safety measures to assess quality of various operational alternatives through microsimulation has brought new perspectives to this field. Several microscopic simulators are currently equipped to generate vehicular trajectory data that can be post-processed by Surrogate Safety Assessment Model (SSAM) (Gettman et al., 2008) to provide surrogate safety estimates. Although ability to estimate surrogate safety measures does not necessarily translate to an ability to predict accidents, the relationship between surrogate safety metrics and field crashes are similar to other conventional methods and their estimation of crashes.

Signal timing optimization tools are historically used to optimize signal timings to reduce traffic delay, stops, and other measures of traffic efficiency. The concept of optimizing signal timings to directly reduce safety metrics or their surrogate measures is not present in current signal timing optimization practice. Unlike metrics representing efficiency of traffic operations, commonly used signal timing optimization tools (such as Synchro, TRANSYT-7F, and PASSER) are not equipped to evaluate impacts of signal timings on surrogate safety metrics. Although a recent study addressed impacts of signal timings on surrogate safety measures (Sabra et al., 2010), there are many questions which remain unanswered.

This study advocates a fresh approach to integrating the evaluation of surrogate safety measures and stochastic optimization of signal timings. VISSIM microsimulation software (PTV, 2010), Surrogate Safety Assessment Model (SSAM) (Gettman et al., 2008), and VISSIM-based Genetic Algorithm for Optimization of Signal Timings (VISGAOST) (Stevanovic et al., 2007) have been integrated in a framework to minimize selected surrogate safety measures by adjusting signal timings. The optimization process generates signal timings which minimize surrogate safety measures thus representing conditions which reduce risk of potential real-world crashes.

Since minimization of some surrogate safety measures (e.g. number of conflicts) may be accompanied by a reduction in traffic efficiency, this study investigates various options to increase safety benefits of signal timing plans without worsening traffic performance. One of these options is use of a multi-objective optimization where an optimal solution is not a point but a Pareto Front which gives users an opportunity to find the best trade-off between (surrogate) traffic safety and traffic efficiency.

LITERATURE REVIEW

Traffic Safety and Retiming of Traffic Signals

When evaluating impacts of signal timings on road safety, the main focus is often on intergreen (yellow + all-red) times, while other signal timing parameters get little attention. Impact of intergreen on red-light running and dilemma zones is well documented (see, for example, Zimmerman and Bonneson, 2005). However, very few studies have estimated the direct impact due to other signal timing parameters (such as cycle length, offsets, splits and phase sequence). One of the first such studies was conducted by Moore and Lowrie (1976), who investigated the impact of traffic signal coordination on number of traffic accidents in the field. They compared frequency of accidents from areas with and without coordinated signals and estimated a 23% reduction in accidents following traffic signal coordination.

Nowadays, when signals are retimed the practice by consultants (Howard/Stein-Hudson Associates, Inc., 2010) is to apply a crash reduction factor. However, this approach is not very reliable because crash reduction rates may be based on a limited number of research studies. The Highway Safety Manual (HSM, 2010) recognizes that there is a gap in knowledge in this field and it reports that most signal timing adjustments (including coordination of traffic signals) have unknown effects on crashes.

Surrogate Safety Measures and Field Crash Statistics

The historical account of correlating traffic conflicts with traffic accidents is relatively long (Perkins and Harris, 1967; Zegeer and Deen, 1978) but unfortunately somewhat unsuccessful. While researchers have not been able to show that traffic conflicts (either from microsimulation or from the field) are strongly correlated to traffic accidents, three major arguments are used to justify continued interest in analyzing traffic conflicts as a means to estimate traffic accidents:

- Although using traffic conflicts to estimate accidents is not significantly better than using past accident data, both approaches generally produce similar results (Migletz et al., 1985; Gettman et al., 2008).
- Conflicts should be used to estimate an expected rate of accidents, as opposed to predicting the actual number, because actual numbers can significantly vary by year (Migletz et al., 1985).
- Other, non-safety related variables (e.g. volume, speed or occupancy) are not reliable estimators of accident rates either (Zhou or Sisiopiku, 1997).

Surrogate Safety Measures from Microscopic Simulations

One of first studies using a widely-available simulation model (for earlier studies see Cooper and Ferguson, 1976; Fazio and Rouphail, 1990; Kosonen and Ree, 2000) was conducted in 2002 by Drummond et al. when the authors found a high correlation ($0.54 \leq R^2 \leq 0.89$) between traffic efficiency performance measures (e.g. delays and stops) from simulation and field crash rates.

A major breakthrough in research on surrogate safety measures based on microsimulation outputs was achieved when Gettman and Head (2003) developed functional requirements and algorithms for a software tool that analyzed surrogate measures generated by a simulation model. This research led to development of publicly-available SSAM software a few years later (Gettman et al., 2008).

Several other studies followed with their own developments of surrogate safety measures or proposed modifications to existing ones. Klunder et al. (2006) proposed development of a better framework for generating safety performance measures based on the Multi-Agent Real-time Simulator (MARS) interfaced with Quadstone Paramics microsimulation software. Ozbay et al. (2008) emphasized a need for well-calibrated and validated microsimulation models from which safety surrogate measures are collected. In fact, they developed a new crash index and modified an existing one, and proved that both indices match field data both temporally and spatially. Tarko et al. (2009) synthesized concepts, key studies, and definitions of surrogate safety measures and identified future research directions.

A recent study has furthermore comprehensively addressed the impact of signal timings on surrogate safety measures using Surrogate Safety Assessment Methodology (SSAM) to evaluate simulated scenarios (Sabra et al., 2010). However, study by Sabra et al. (2010) was performed within a framework that did not guarantee consistent outcomes because signal timings optimized in Synchro (a deterministic tool) were evaluated in VISSIM (a stochastic environment) where their performance may not have been optimal (see Stevanovic and Martin, 2007; and Mulandi et al., 2010). In addition, authors did not perform any optimization; instead, they incrementally changed signal timings and evaluated their individual impact on safety surrogate measures.

Multi-objective Evolutionary Optimizations of Signal Timings

There is a long list of GA-based signal timing optimizations which were based on single-objective searches (see for example literature review in Stevanovic et al., 2008). Here authors focused on a few key studies which implemented evolutionary multi-objective optimization to retime traffic signals. Sun et al. (2003) applied NSGA-II to optimize delay and stops for an isolated intersection under two-phase control. NSGA-II obtained a close approximation to the Pareto set while using analytical formula to determine delay and stops. Abbas et al. (2007) applied NSGA-II to a small three signal network while choosing signal settings from a predetermined set obtained from a single objective optimization at different cycle lengths. Thus the multi-objective optimizer only considered variations in cycle length, simplifying the exercise considerably. Kesur (2010) investigated and suggested a multi-objective optimization when the number of optimization variables increases while delay and stops are evaluated through a microscopic traffic simulator.

Summary of Past Research

Research studies do not presume that surrogate safety measures are reliable estimators of real-world crashes, rather they consider them valid measures with a lot of potential for improvement. Available studies on surrogate safety measures from simulation modeling show a continued interest from the research community. No current signal optimization tool offers an estimate of surrogate safety measures in its optimization of signal timings. Furthermore, there have not yet been any attempts to conduct such optimizations. Except for a recent FHWA report (Sabra et al. 2010) there are practically no studies that address impacts of (non-intergreen) signal timings on surrogate safety measures. Multi-objective evolutionary optimizations are widely used methods in optimization of signal timings although (surrogate) safety has not yet been part of those optimizations.

VISSIM-SSAM-VISGAOST FRAMEWORK

The following describes the integration of VISSIM, SSAM, and VISGAOST to optimize signal timings to reduce total number of conflicts (as a surrogate safety measure obtained from SSAM).

VISSIM

VISSIM is a microscopic, time step and behavior-based model developed to simulate urban traffic and public transport operations. The program can analyze vehicle operations under different lane configurations, traffic composition, traffic signals, and public transport stops. VISSIM uses the psycho-physical driver behavior model developed by Wiedemann (PTV, 2010) whose basic concept is that the driver of a faster moving vehicle decelerates when approaching a slower moving vehicle according to the driver's individual perception threshold.

SSAM

The Surrogate Safety Assessment Model (SSAM), a software application sponsored by FHWA, provides safety analysis for simulation-based comparative studies (Gettman et al., 2008). The software processes vehicle trajectory data exported from microscopic traffic simulation models to estimate the frequency and severity of various types of conflicts.

By definition, a conflict represents an observable situation in which two or more motor vehicles approach each other in time and space to such an extent that there is risk of collision if their movements remain unchanged (Amundsen and Hyden, 1977). To determine if a vehicle-to-vehicle interaction is classified as a conflict, the threshold values for two surrogate measures of safety are applied: time-to-collision (TTC) and post-encroachment time (PET). SSAM identifies four types of conflicts: crossing (angle), lane-changing, rear-end and unclassified. The type is determined based on the conflict angle, and link and lane information. A conflict angle for a pair of vehicles is calculated based on the angle at which these vehicles converge to a hypothetical collision point. For each conflict, SSAM computes a number of corresponding surrogate measures of safety (TTC, PET, etc.) along with their summaries (mean, max, and variance).

The SSAM approach was validated using a database of 83 four-legged urban signalized intersections (Gettman et al., 2008). The intersections were modeled in VISSIM and the safety was assessed with SSAM. The research included theoretical validation, field validation and sensitivity analysis. The assessments of SSAM showed accuracy similar to that of traditional theoretical crash-prediction equations, which are based on average daily traffic volumes. Thus, the SSAM approach exhibits promise to provide significant support to evaluations of traffic engineering alternatives without expensive field crash studies (Gettman et al., 2008).

VISGAOST

VISGAOST is an optimization program that optimizes signal timings of traffic controllers based on their performance in VISSIM microscopic simulation. VISGAOST bases its optimization on the stochastic nature of Genetic Algorithms (GAs). The general structure of VISGAOST GA optimization is well documented (Stevanovic et al., 2008). The basic version of VISGAOST is written in C++ and relies on VISSIM's input and output files (PTV, 2010). The key part of the VISGAOST program is a simple GA similar to other GAs used for signal timing optimization (Goldberg, D.E., 1989).

The first version of VISGAOST enabled the optimization of all four basic signal settings i.e. cycle, offset, splits and phase sequence. Results from the first tests and evaluations confirmed that VISGAOST can provide a better timing plan than those from the field (Stevanovic et al., 2007). Further, the results showed that the GA-optimized plan was better in VISSIM than the timing plan generated by the traditional optimization tool SYNCHRO.

VISGAOST application was further extended to enable optimization of: transit signal priority settings (Stevanovic et al., 2008), signal timings to minimize fuel consumption and vehicular emissions estimated by Comprehensive Modal Emission Model (CMEM) (Stevanovic et al., 2009), among others.

VISSIM-SSAM-VISGAOST Integration

Figure 1 shows the integration of VISSIM, SSAM, and VISGAOST to find signal timings which reduce surrogate safety measures. The program previously used for similar optimizations was modified to accommodate a new SSAM interface. The optimization process starts with VISGAOST generating an initial population of signal timings, which is seeded by the existing set of signal timings from field. Each generated signal timing plan is evaluated in VISSIM, which generates both network-wide measures of effectiveness and trajectory data for each vehicle (where outputs are required for subsequent optimization steps).

The trajectory data file (*.trj) is processed by SSAM to identify the frequency, severity and types of conflicts (Gettman et al., 2008). In the next step the number of conflicts from SSAM is manipulated with some VISSIM performance measures to produce a meaningful objective function for VISGAOST optimization (more about development of the objective function is provided later). This objective function is then minimized through the Genetic Algorithm iterative procedure by evaluating various combinations of signal timings from intersection controllers (Stevanovic et al., 2008). The whole process is then repeated until the predefined termination criterion is met (using a number of repetitions or convergence of the solutions).

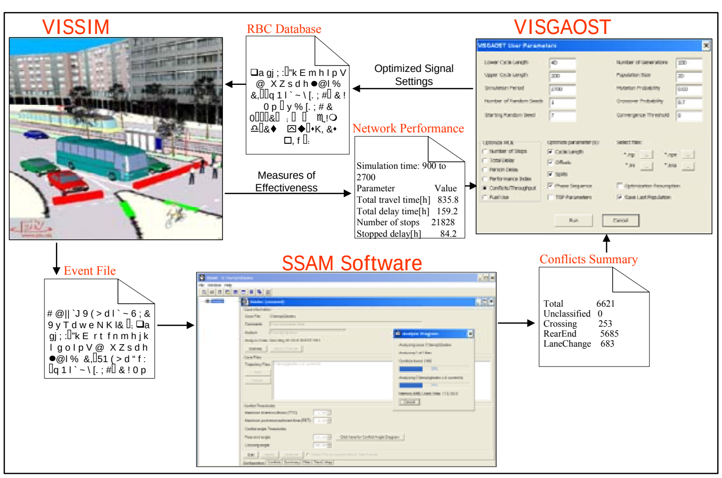


Figure 1 VISSIM-SSAM-VISGAOST Integration

OPTIMIZING SIGNAL TIMINGS TO REDUCE SURROGATE SAFETY MEASURES

When optimizing signal timings (in stochastic platforms, such as VISSIM) with a goal to reduce some of the unconventional performance measures (e.g. fuel consumption and number of conflicts) it is necessary to combine these unconventional objective functions with traditional performance measures (e.g. delay, stops, and throughput) to get meaningful objective functions. Unlike delay, stops and throughput, metrics such as fuel consumed or total number of conflicts are not directly proportional to efficiency of traffic. For example, less fuel is consumed by standing traffic than by traffic flowing at a speed of 45 mph. Similarly, the number of conflicts in jammed traffic is minimal because vehicles cannot move freely. An attempt to minimize fuel consumption or number of conflicts when these are used as sole objective functions in an evolutionary optimization process would inevitably lead to solutions (or a set of signal timing parameters) that would block at least a portion of (if not all) traffic and decrease overall traffic activity (and efficiency). So to get meaningful results, metrics such as fuel consumption and number of conflicts, which are indirectly proportional to traffic efficiency, need to be combined with metrics directly proportional to traffic activity. For this reason fuel consumption and crash rates (as an example of safety metrics) are usually expressed per mile of travel.

For the purpose of optimizations conducted in this study authors used vehicular throughput as a measure of traffic activity to be combined with number of conflicts in the optimization objective function. Vehicular throughput in VISSIM is referred as "number of vehicles that have left the network"); it is highly correlated with total miles traveled (R^2~0.9) and as such it is a good representative of traffic activity/efficiency.

Four optimizations were conducted in this study. Three of them were single-objective optimizations with various objective functions. The fourth optimization was a multi-objective optimization where solutions in two-dimensional space were sought. The following describes each of the conducted optimizations.

Single-objective (conflicts/throughput ratio) optimization

In the first optimization scenario the objective function was simply a ratio between total number of conflicts and throughput as shown in equation (1). Soon after this optimization started it was obvious that this approach was not going to generate satisfactory signal timings. For some of the traffic movements in the network each vehicle could generate more than one conflict. Hence, if such a vehicle is stopped by a traffic signal long enough, that vehicle would not leave the network and the final throughput would be reduced. However, multiple conflicts could be avoided by keeping this vehicle stopped. Thus, although the optimization algorithm could recognize that such a signal timing plan is good (since rate of reducing number of conflicts is higher than rate of reducing throughput) such a solution is unacceptable.

$$CTR = \frac{C}{T} \tag{1}$$

where:
CTR - conflicts/throughput ratio
C - total number of conflicts generated during simulation
T - total number of vehicles that have left the network (throughput)

Single-objective (conflicts/throughput-with-penalties ratio) optimization

After observing experiments during the first optimization authors were challenged to assign a weight to throughput and thus increase its importance in the conflict/throughput ratio, which was used as an objective function, or to impose a penalty (within GA optimization procedures) for any signal timing plan that reduces throughput. The latter option was chosen primarily because there was no basis for an appropriate weight for throughput in a conflict/throughput ratio. Introducing a very high weight could result in a small reduction in number of conflicts whereas introducing too low a weight could unacceptably reduce throughput. Hence, signal timing plans with low throughputs were assigned low probabilities of being selected (for recombinations with other timing plans) during the GA procedure. A general GA procedure for single-objective optimization in VISGAOST has been presented elsewhere (Stevanovic et al., 2007). Here authors explain only the imposition of penalties to signal timings which significantly reduce throughput.

First, all of the signal timing plans are sorted and ranked based on ratio of total number of conflicts to throughput. Then, temporary selection probabilities for each timing plan are determined using normalized geometric selection functions:

$$p_i = q`*(1-q)^{r-1} \tag{2}$$

$$q` = \frac{q}{1-(1-q)^N} \tag{3}$$

where:
q - probability of selecting the best individual timing plan
r - rank of the individual timing plan (with best equals 1)
N - population size

The final probabilitieis were assigned to each signal timing plan i in the following way:

$$P^{final}{}_i = \begin{cases} p_i, if\ T_{min} \le throughput_i \\ p_{N,}\ if\ throughput_i < T_{min} \end{cases} \tag{4}$$

$$T_{min} = \frac{98*T_{initial}}{100} \tag{5}$$

where:
T_{min} = lower throughput boundary to define selection probability
$T_{initial}$ = throughput of the initial timing plan

It should be noted that the adopted approach limits the reduction of throughput to a maximum of 2% with respect to the initial throughput based on field signal timings. Although this limit is user configurable it should be noted that even small reduction in overall throughput may represent unnecessary blockage of certain traffic movements.

Single-objective (Performance Index) optimization

Optimization with Performance Index (PI) as an objective function was conducted mainly as a base-case scenario. PI (equation 6) is a linear combination of stops and delays and it represents one of the most commonly used objective functions when optimizing signal timings to achieve the best traffic efficiency. By optimizing with PI and comparing results of such optimizations to others, authors sought to investigate how much (surrogate) traffic safety is 'lost' due to excellent traffic efficiency, or vice versa.

$$PI = \sum_i d_i + w/3600 \cdot \sum_i s_i \tag{6}$$

Where d_i and s_i represent delay and number of stops (respectively) for each vehicle i which completes its trip in the network during the simulation period. w represents weight given to each stop where most optimization programs (such as Synchro and Transyt-7F) assign w value of 10.

Multi-objective (Conflicts & Throughput) Optimization

The last optimization experiment was a multi-objective optimization, where a solution is a set of points in the conflict-throughput domain which shows trade-offs between these two variables. Need for this type of optimization arose when it was observed that, in spite of the fact that throughput reduction was strongly discouraged by imposed penalties in the previous optimization, the best solution had a lower throughput than the initial solution. There was a need to find out whether it would be possible to reduce the number of conflict points while not worsening throughput. Also, trading (surrogate) safety for traffic efficiency is an intriguing approach. Not many signal timing professionals, responsible for operations and maintenance of traffic signals, would opt to chose (knowingly) a solution that indicates safety aspects of signal timing design may be worsened. For this reason, it is important to develop robust solutions that give professionals opportunities to adopt signal timings which improve traffic efficiency without worsening traffic safety (from its current state).

Multi-objective optimization is defined as a process where several (usually two), possibly conflicting, objectives are satisfied. In mathematical terms, multi-objective optimization can be defined as a vector of decision variables which satisfies constraints and optimizes a vector function whose elements represent objective functions. These functions form a mathematical description of performance criteria that are usually in conflict with each other. Hence, the term "optimize" means finding a solution with values of all objective functions being acceptable to the decision maker (Osyczka, 1985).

With multiple objective functions, the notion of 'optimum' changes because it is important to find good compromises, or trade-offs, rather than a single solution. The general notion of a multi-objective optimum was introduced by Vilfredo Pareto (Pareto, 1896) with its mathematical formulation given as follows:

> A vector of decision variables $\vec{x}^* \in F$ is *Pareto optimal* if there does not exist another $\vec{x} \in F$ such that $f_i(\vec{x}) \le f_i(\vec{x}^*)$ for all i = 1, ... , k and $f_i(\vec{x}) < f_i(\vec{x}^*)$ for at least one j.
> Where F denotes the feasible region of the problem.

A *Pareto optimal* set represents solutions which correspond to vectors $\vec{x}^*$, which are called *nondominated* solutions. Mathematically, *Pareto dominance* can be described as:

A vector $\vec{u} = (u_1,...,u_k)$ is said to dominate $\vec{v} = (v_1,...,v_k)$ (denoted by $\vec{u} \preceq \vec{v}$) if and only if *u* is partially less than *v*, i.e., $\forall i \in \{1,...,k\}, u_i \leq v_i \wedge \exists i \in \{1,...,k\} : u_i \leq v_i$.

By definition, solution A dominates solution B if solution A is no worse in all objectives than solution B and provides an improvement in at least one objective. Considering this definition, the best solutions are always ones that are *nondominated* by other solutions. *Pareto Front* represents a plot of objective functions whose *nondominated* vectors are in the *Pareto optimal* set.

In this research, the multi-objective optimization is implemented and applied to signal settings optimization problems to find timing plans with the best compromises between number of conflicts and throughput. The optimal trade-off between the two competing objectives is presented with an approximation of the *Pareto Front*. Since the true *Pareto Front* is unknown for this problem (due to the stochastic nature of evolutionary algorithms based on stochastic traffic simulation), multi-objective optimization aims to approximate this set.

Details of GA procedure deployed within VISGAOST are presented elsewhere (Stevanovic et al., 2007). Here, authors focus on changes introduced into the previous GA structure to enable multi-objective optimization within VISGAOST. The main differences are related to selection and the elitism operations within GA. The new selection favors "fitter" solutions for reproduction, but the fitness is determined based on the *nondominated* ranks of competing objectives, as opposed to being based on a single-objective value. A process of ranking solutions starts when the set of *nondominated* individuals/solutions in the population is assigned a rank of 1. This set represents a *Pareto Front* for the current population. Then the non-dominated individuals in the remaining set of solutions are assigned a domination rank of 2, etc. The basic steps required to rank a whole population *p* are given below. One should note that the rank of all timing plans which are members of a *nondominated front* f^r, is *r*. Obviously, the *nondominated front* f^1 of a population represents the *Pareto Front* of that population.

Step 0: *Initializing*
- *p,* population of timing plans
- *r*, rank of current non-dominated front
- f^r, current non-dominated front
- $r = 1$

Step 1: *Testing Termination Criterion*
- IF ($p = \emptyset$)
  - **Stop and Terminate the Search**
- ELSE
  - $f^r = \{tp^l\}, tp^l \in p$
  - GO TO **Step 2**

Step 2: *Searching for Non-dominated Front*
- FOR $\forall\ tp^k\ (tp^k \in p \wedge tp^k \notin f^r)$
  - $f^r = f^r \cup \{tp^k\}$

FOR $\forall$ tp^m $(tp^m \in f^r \wedge tp^m \neq tp^k)$

IF ((conflicts(tp^k) < conflicts(tp^m)) $\wedge$
(throughput(tp^m) < throughput(tp^k)))

THEN $f^r = f^r \setminus \{ tp^m \}$

ELSE IF ((conflicts(tp^m) < conflicts(tp^k)) $\wedge$
(throughput(tp^k) < throughput(tp^m))

THEN $f^r = f^r \setminus \{ tp^k \}$

Step 3: *Reinitializing*

$r = r+1$

$p = p \setminus f^r$

GO TO **Step 1**

In the next step, the binary tournament selection is conducted during which N (population) pairs of timing plans are randomly selected. The timing plans with the lower domination ranks are chosen to contribute to the next generation. If both selected timing plans have the same rank, the final choice is determined randomly. The binary tournament selection is repeated until a mating pool, of the same size as the population, is obtained. Further creation of a new population using the four basic GA operations is the same as described for single-objective optimization (Stevanovic et al., 2008).

Once the child population is created, it is combined with the parent population and the domination ranks are reassigned. Finally, the elitist replacement scheme finds the N best individuals within the united population and keeps them for future generation. However, the selection process of N best individuals is not necessarily trivial. If the size of the *nondominated front* f^r is smaller than N, all of the *nondominated* timing plans become members of the new population. The remaining members are chosen from subsequent *nondominated fronts* in order of their ranking until the new population is complete. Conversely, if the size of the *nondominated front* f^r is higher than N, N timing plans for the new population are chosen randomly (Deb et al., 2002). The basic operations in the multiple-objective optimization process performed by VISGAOST are summarized below. The process also includes new procedures to read/write signal timings from/to Ring-Barrier Controllers (RBC) in VISSIM (as opposed to previous structures of NEMA controllers), which is also an original contribution of this research.

Step 0: *Initializing*

G, total number of generations

T, total number of timing plans per generation

ε, convergence threshold

i, current number of population

pf, *Pareto Front*

$i = 0$

$pf = \emptyset$

Generation of initial population p^i of timing plans tp^k, $\forall k \in [1,..T]$

- read field timing plan tp^1 from RBC database
- generate tp^k, $\forall k \in [2,..T]$
- rank population p^i
- define pf = paretoFront(p^i)

Step 1: *Evaluating Population*

Evaluation of $tp^k \in p^i$, $\forall\, k \in [1,..T]$

- write tp^k to RBC database
- simulate (and evaluate network performance of) tp^k
- estimate safety measures for tp^k

Step 2: *Testing Termination Criterion*

IF ($i = G$)

Stop and RETURN *pf*

ELSE

GO TO **Step 3**

Step 3: *Generating New Population*

$i = i + 1$

Generation of new population p^i

- generate p^i through GA-operations
- form combined population $p^u = (p^{i-1} \cup p^i)$
- rank population p^u
- define p^i = (T best timing plans from p^u)
- define pf = paretoFront(paretoFront(p^u) $\cup$ pf)

GO TO **Step 1**

A CASE STUDY

Study Network – Glades Rd in Boca Raton, FL

A 3.3-mile section of Glades Road, located in Boca Raton, FL was used as a test bed for optimization experiments. This section of Glades Road, shown in Figure 2, has 12 actuated-coordinated signalized intersections and represents one of the busiest arterial sections in the city.

Traffic volumes, previously collected by City of Boca Raton at a few tube-count stations, were used to identify the busiest period during the day which was found to be from 3:30 PM to 6:30 PM. Turning-movement counts for about 90% of all turning movements in the network were collected by observing video recordings from relevant cameras in the field. A few missing traffic counts were obtained either from traffic count data sets collected in 2005 or from flow-balancing spreadsheets. Field travel times were collected by floating-car technique with GPS units.

All of the data were collected during the PM peak period on Tuesdays, Wednesdays and Thursdays under fair weather and dry pavement conditions, during a busy season (November-May) in Boca Raton. City of Boca Raton provided field signal timings. Data from 3-hour video recordings were reduced and 1-hour traffic flows from the busiest hour (generally from 4:45 to 5:45 PM) were entered into simulation models.

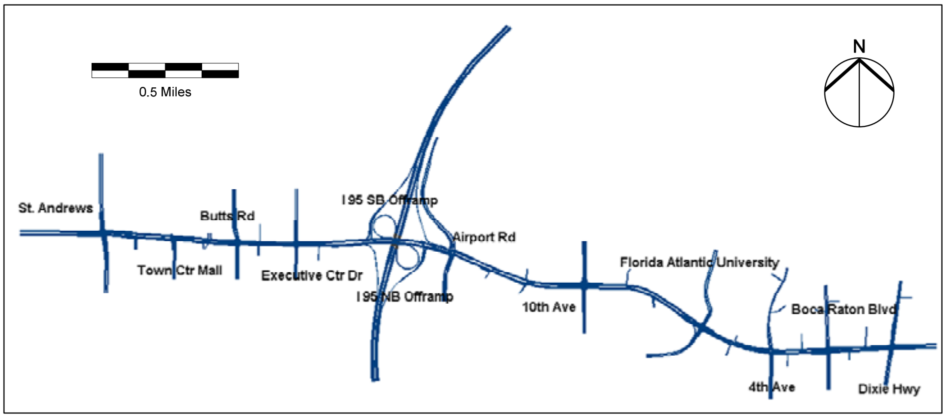


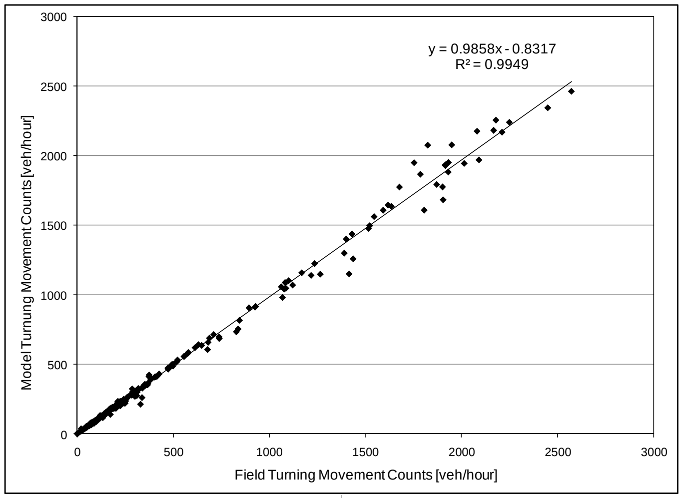
Figure 2 VISSIM model of Glades Road in Boca Raton, Florida

Building, Calibrating, and Validating the VISSIM Model

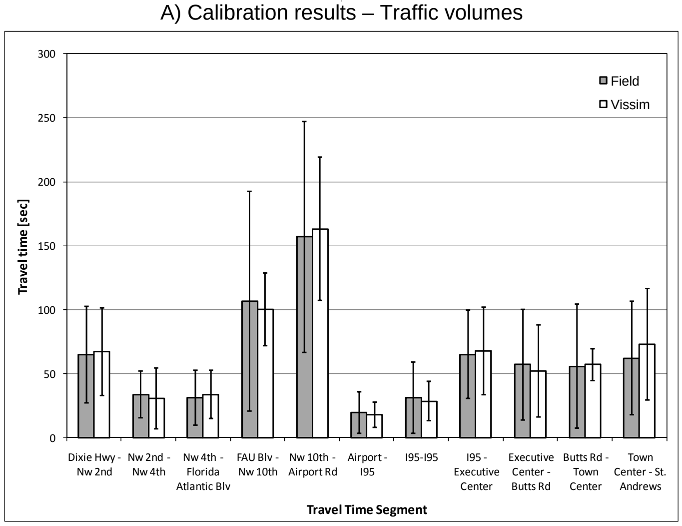
The model was carefully checked for completeness and accuracy by ensuring that geometry, volumes, link speeds and signal timings were the same as those in the field. Calibration of the model was based on traffic volumes, link speeds, and GPS travel times. Traffic inputs and routing decisions were adjusted in VISSIM to accurately resemble turning movement counts observed in the field. The model was calibrated at a few turning movements by adjusting the saturation flow rate (via the additive and multiplicative parts of the desired safety distance) and lane change parameters (via waiting time before diffusion, maximum deceleration and minimum headway). Also, during the calibration process, desired and maximum acceleration and deceleration distributions were adjusted in VISSIM to resemble the acceleration and deceleration data from the field. Figure 3 shows results of calibration and validation processes for three performance measures: traffic volumes and travel times (calibration), and queue lengths (validation).

VISGAOST Optimizations and VISSIM Simulations

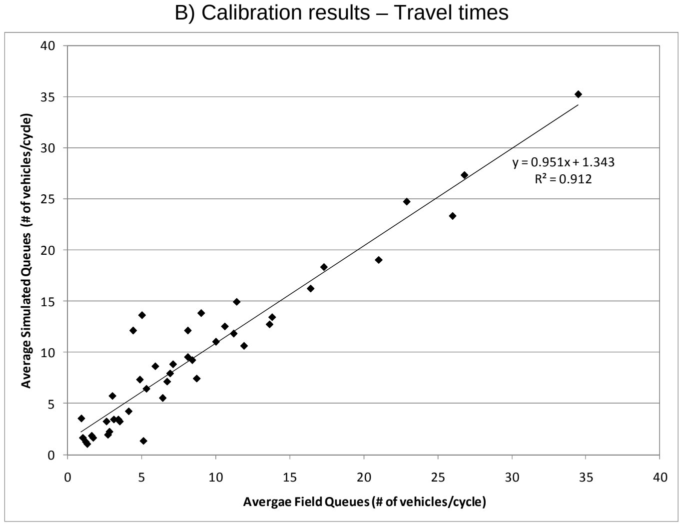
Four aforementioned optimization experiments were conducted; all starting from the same base – field signal timings. Each optimization was based on evaluations of traffic performance and/or surrogate safety measures accumulated during 30 minutes of simulation time with an additional 15 minutes of warm up time. Each optimization had 2000 evaluations of various signal timing plans – 20 signal timing plans were operated through GA procedures for each of 100 generations. All VISSIM evaluations within VISGAOST optimizations were executed for a single random seed (for the purpose of computing efficiency). The GA parameters used were default VISGAOST parameters which were justified in previous studies (Stevanovic et al., 2007). In total, optimization experiments took more than a month on a couple of personal computers. After optimizations, signal timings were evaluated in 10 randomly seeded simulation runs to check robustness of the best signal timing plans.



A) Calibration results – Traffic volumes



B) Calibration results – Travel times



C) Validation results – Queue lengths

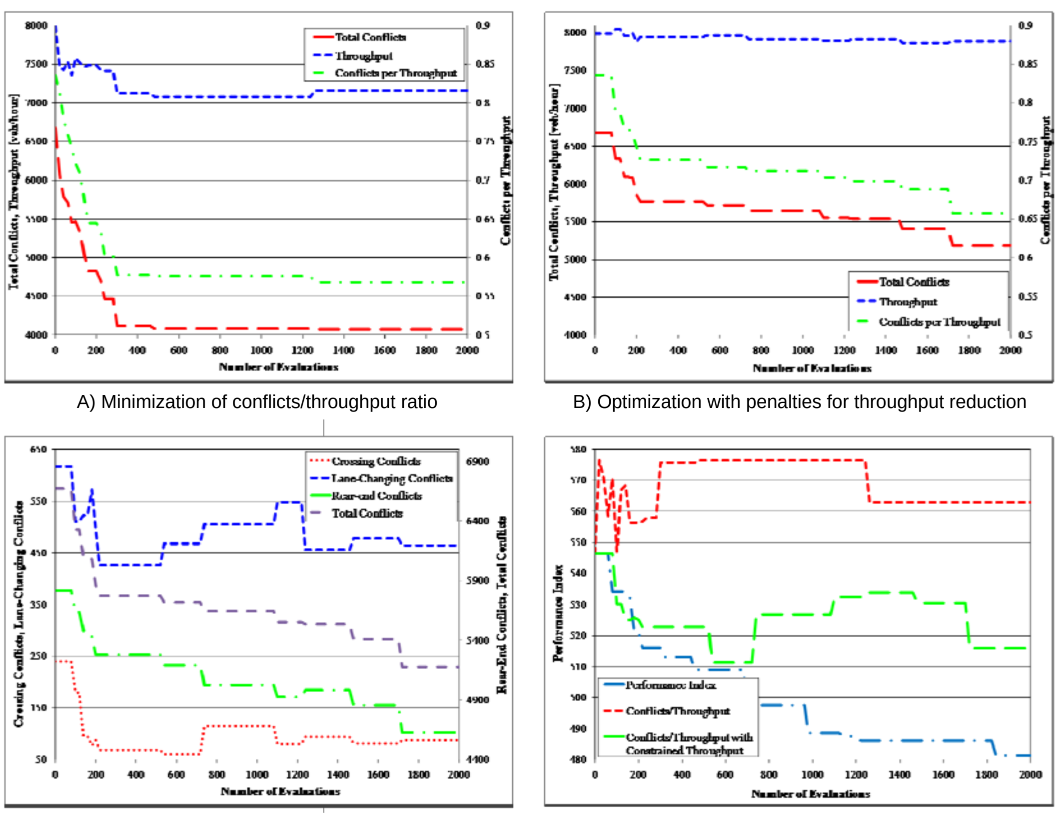
Figure 3 Match between field and model: calibration and validation

RESULTS AND DISCUSSION

Figure 4 shows results of single-objective optimizations. Each of the four charts in Figure 4 shows how the objective function evolved through the course of optimizations (100 generations/2000 evaluations). Part A) of Figure 4 shows that while conflicts are being reduced with better signal timings the throughput is being reduced as well. Conflicts are reduced at a greater rate than throughput, which provides a good CTR although reduction in throughput may not be acceptable due to blockage of certain traffic movements. Part B) of Figure 4 shows results of optimization where reduction in throughput is penalized. Although the reduction in number of conflicts is still very significant (around 20%) it is only half of what was achieved in the previous case, with significant reduction in throughput. The chart also shows that the modified procedure for signal timing plan selection was successful in limiting reduction of throughput.

Part C) of Figure 4 shows how individual conflicts vary during the course of optimizations with penalized reduction in throughputs. One can observe that rear-end conflicts are dominating the total number of conflicts and thus control the behavior of the objective function during the optimization process. It is interested to note (see for example the interval between the 500th and 1300th evaluation) that some signal timing plans reduce rear-end conflicts while at the same time increase either lane-changing or crossing conflicts, or both.

Finally, Part D) of Figure 4 shows traffic efficiency qualities of signal timing plans optimized to reduce conflict/throughput ratios. Both signal timing plans (with and without constrains in throughput) perform worse than signal timings optimized specifically for efficiency (performance index). However, these results are expected since it is clear that benefits in



A) Minimization of conflicts/throughput ratio

B) Optimization with penalties for throughput reduction

C) Various conflicts during optimization

D) Variations of PIs in three optimizations

Figure 4 Results of various optimizations reducing the number of vehicular conflicts cannot be achieved without sacrificing some traffic efficiency.

The final signal timings from three single-objective optimizations were evaluated again in VISSIM for 10 various random seeds. This was necessary because evaluations of signal timings in VISSIM are based on a single random seed in the optimization process. So, before results are reported these signal timings need to be exposed to the stochastic nature of simulation runs before final conclusions about their performances are drawn. So all signal timings were evaluated once again in VISSIM with throughput, total delay and number of stops reported along with basic statistics. Also, outputs from 10 randomly-seeded VISSIM runs (with the best signal timings for each optimization) were post-processed again in SSAM. SSAM's estimates of conflicts were analyzed. Means and standard deviations from these statistics are presented in Table 1.

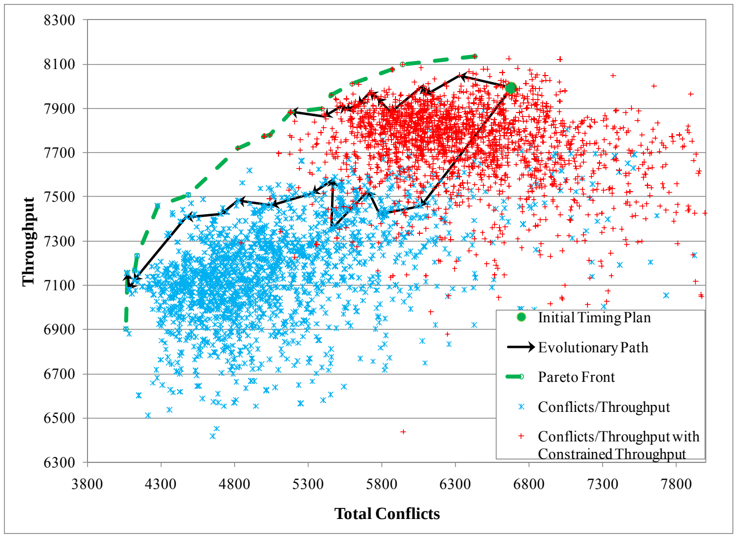
Table 1 Measures of effectiveness from 10-runs tests

MOE Optimized	Throughput		Number of Conflicts		Performance Index	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Initial (No Optimization)	8097	75	6680	284	548.56	12.88
Performance Index	7750	71	6823	713	539.97	24.32
Conflicts/Throughput	7094	55	5203	645	608.76	25.12
Conflicts/Throughput & Penalties	7938	66	6253	478	541.63	18.79

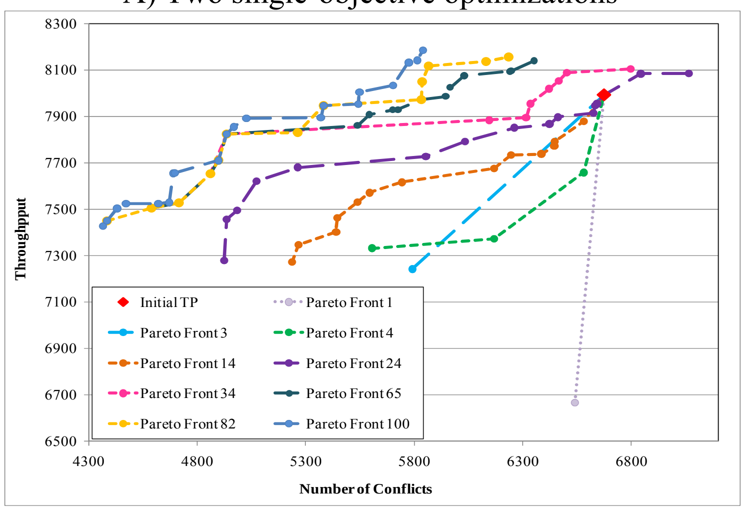
Results of the additional simulation runs, as in similar previous studies, reduced differences observed in Figure 4. So, the statistics form Table 1 show that the best 'safety' signal timing plan yields similar traffic efficiency (PI) as the best 'traffic efficiency' signal timing plan. Moreover, the best 'safety' timing plan reduced number of conflicts for about 10% and slightly increased throughput, when compared to the best 'traffic efficiency' signal timings. One should note the significant difference between results in Table 1 and Figures 4 and 5. This difference could be annulled if multiple randomly-seeded runs were performed during the optimization process. However, high computational requirements still prohibit such an approach to be cost effective.

Part A) of Figure 5 shows all evaluated solutions in the conflict-throughput domain during the first two single-objective optimizations. It is visible that both optimization search paths (along the dotted arrow line) led to the solutions which lie on the approximation of the Pareto Front for these two performance measures. However, one should note that this approximation of the Pareto Front was created after the fact, when optimizations were completed. Nevertheless, the chart helps visualize search processes, and justifies both the decision to introduce optimization with penalties for low throughputs and the decision to apply a multi-objective optimization.

One should take note of several solutions from the second single-objective optimization (with red crosses), which belong to the Pareto Front, located right and above the optimal solution but left and above the initial solution. These solutions, with higher throughput and fewer conflicts than initial solution, represent real gains for these experiments. By adopting any of the signal timing plans representing these solutions, a traffic signal engineer would improve safety (by reducing number of conflicts) without compromising the efficiency (throughput) of its current (initial) signal timings plan.



A) Two single-objective optimizations



B) Multi-objective optimization

Figure 6 Approximations of non-dominated (Pareto) fronts after/during optimizations

Part B) of Figure 5 shows results of the multi-objective optimization. Initial, final, and eight other arbitrarily-chosen approximations of the Pareto Front are shown. The figure shows how sets of nondominated solutions evolved during 100 generations of the evolutionary optimization process. The final approximation of the Pareto Front is also better than a post-optimization approximation of the Pareto Front shown in part A) of Figure 4, which confirms success of the multi-objective optimization algorithm to find better Pareto Front approximations.

When it comes to 'real' differences between initial and optimal signal timing plans there were no findings that could be easily drawn from the two sets of signal timings. According to Sabra et al. (2010) higher cycle lengths facilitate better coordination and fewer rear-end conflicts. Authors did observe somewhat similar findings, as shown in Table 2. The largest differences were observed in offsets although no trends were observed between offsets and vehicular conflicts. A linear regression analysis was conducted to find out whether optimal signal timings alter phase splits in such a way that there is a trend between splits and some conflicts (e.g. increase in left-turn green may reduce crossing conflicts). However, such analysis yielded very low correlation factors (for all turning movements) showing that there were no such trends.

By looking at Table 2 one may speculate that better signal timings may be achieved (by altering some offsets and splits) than the ones obtained in the optimization process. The stochastic optimization with GA is a process that goes through thousand of combinations and does not guarantee a global optimum. However, we provide unaltered results in Table 2 to show both advantages and disadvantages of the GA optimization process.

Table 2 Initial versus optimized signal timings

	Intersection	Cycle [s]	Offset [s]	Phase Splits [%] 1	2	3	4	5	6	7	8	Phase Sequence
INITIAL SIGNAL TIMINGS	St. Andrews	180	52	13	48	13	26	16	45	13	26	1 2 3 4 5 6 7 8
	Town Center Mall	180	54	-	71	-	12	19	52	17	-	2 4 5 6 7
	Butts Rd	180	145	12	44	12	32	13	43	20	24	1 2 3 4 6 5 7 8
	Executive Center	180	148	11	53	14	22	20	44	14	22	1 2 3 4 5 6 7 8
	I-95 SB Ramp	180	110	-	61	-	-	-	61	-	39	2 6 8
	I-95 NB Ramp	180	91	-	69	-	31	-	69	-	-	2 4 6
	Airport Rd	180	90	17	49	9	25	9	57	24	10	1 2 3 4 5 6 7 8
	NW 10th Ave	160	130	18	42	10	30	11	49	10	30	2 1 3 4 5 6 7 8
	FAU Blvd	160	34	13	49	-	38	19	43	14	24	1 2 4 6 5 7 8
	NW 4th Avenue	160	24	20	40	-	40	13	47	12	28	1 2 4 5 6 7 8
	Boca Raton Blvd	160	26	18	37	14	31	13	42	13	32	2 1 3 4 5 6 7 8
	Dixie Hwy	150	56	21	31	-	48	13	39	15	33	1 2 4 5 6 8 7
OPTIMIZED SIGNAL TIMINGS	St. Andrews	179	25	22	33	18	27	13	42	24	21	1 2 4 3 5 6 8 7
	Town Center Mall	179	31	-	80	-	10	39	41	10	-	2 4 5 6 7
	Butts Rd	179	167	40	32	9	19	27	45	9	19	1 2 3 4 6 5 7 8
	Executive Center	179	156	9	51	28	12	8	52	24	16	2 1 4 3 5 6 7 8
	I-95 SB Ramp	179	107	-	79	-	-	-	79	-	21	2 6 8
	I-95 NB Ramp	179	76	-	66	-	34	-	66	-	-	2 4 6
	Airport Rd	179	79	7	56	9	28	16	47	20	17	1 2 3 4 5 6 7 8
	NW 10th Ave	185	179	9	13	27	51	8	14	45	33	2 1 3 4 5 6 8 7
	FAU Blvd	185	38	30	42	-	28	9	63	7	21	1 2 4 6 5 7 8
	NW 4th Avenue	185	135	10	32	-	58	9	33	7	51	1 2 4 5 6 7 8
	Boca Raton Blvd	185	114	29	40	7	24	10	59	8	23	2 1 3 4 5 6 7 8
	Dixie Hwy	159	108	25	33	-	42	29	29	9	33	1 2 4 5 6 7 8

CONCLUSIONS

The goal of the study was to present a new integration of traffic simulation, surrogate safety assessment, and signal timing optimization tools. The study describes integration of VISSIM, SSAM, and VISGAOST to optimize signal timings in such a way to achieve minimal estimated number of conflicts while maintaining efficiency of traffic signals. The case study used a network of 12 signalized intersections in Boca Raton, Florida. For this arterial, three single-objective optimizations were completed to determine a balance between safety and efficiency. In addition, a multi-objective optimization was conducted to provide a trade-off curve between (surrogate) traffic safety and traffic efficiency. The most efficient signal timing plan was found using the performance index as the objective function during the GA-optimization. The initial and the three best timing plans were additionally evaluated through VISSIM and SSAM for 10 randomly seeded traffic patterns. Based on the described integration process and observed findings, it is concluded that:

- The single-objective optimization that used a ratio of number of conflicts to throughput significantly decreases the rate of conflicts. However, the decrease in throughput is not negligible. Thus, this objective function cannot be used as a reliable objective function to find the timing plan with the optimal balance between safety and efficiency.
- The optimal balance between safety and efficiency was reached using the ratio of number of conflicts to throughput as the objective function while penalizing the inefficient timing plans during optimization. When compared to initial signal timings, the estimated number of conflicts is decreased by 7%, while throughput was almost maintained at the initial level. When compared to the signal timing plan with the best PI, number of conflicts was reduced by 9% while PI remained almost the same.
- Raw results from the optimization experiments showed even larger benefits in reducing surrogate safety measures but the final results from multiple stochastic repetitions reduced the magnitude of benefits.
- Multi-objective optimization found the best approximation of the Pareto Front between number of conflicts and throughput thus providing a tool that may help signal timing practitioners to prioritize their needs between safety and efficiency when optimizing traffic signals.

Further research is needed to test this approach on a variety of networks and traffic conditions and to find a good composite measure (of surrogate safety measures and traditional traffic metrics) for use in single-objective optimizations. Also, with an increase in computer efficiency, utilization of multiple random seeds during the optimization process will enable better search for more robust signal timings. Finally, further validation of surrogate safety measures and higher fidelity of micro-simulation outputs will increase meaningfulness of practically incorporating safety aspects into design of traffic signal timings.

REFERENCES

Abbas, M.M, H.A. Rakha, and P. Li (2007). Multi-Objective Strategies for Timing Signal systems Under Oversaturated Conditions. *Proceedings of the 18th IASTED (International Association of Science and Technology for Development) International Conference*. Montreal, Canada. 580-585.

Amundsen, F., and Hyden, C. (1977). *Proceedings of first workshop on traffic conflicts*, Institute of Transport Economics, Oslo, Norway.

Cooper, D., and Ferguson, N. (1976). “A conflict simulation model”, *Traffic Engineering and Control*, Vol 17, 306-309.

Deb. K, A. Pratap, S. Argawal, and T. Meyarivan (2002). "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II", *IEEE Transactions on Evolutionary Computation*, Vol. 6, 182-197.

Drummond, K., Hoel, L.A., and Miller, J.S. (2002). *A Simulation-based Approach to Evaluate Impacts of Increased Traffic Signal Density*, Research report of Virginia Transportation Research Council, Charlottesville, Virginia.

Fazio, J. and Rouphail, N. (1990). "Conflict simulation in INTRAS: Application to weaving area capacity analysis", *Transportation Research Record*, Vol. 1287.

Gettman, D. and Head, L. "*Surrogate Safety Measures From Traffic Simulation Models"*, Report No. FHWA-RD-03-050, Federal Highway Administration, Washington, DC, 2003.

Gettman, D., Pu, L., Sayed, T., and Shelby, S. "*Surrogate Safety Assessment Model and Validation: Final Report*", Report No. FHWA-HRT-08-051, Federal Highway Administration, Washington, DC, 2008.

Goldberg, D.E. (1989). "*Genetic Algorithms in Search, Optimization and Machine Learning*". Addison-Wesley- Publishing Co. Inc. Massachusetts.

Highway Safety Manual (HSM). (2010). American Association of State Highway and Transportation Officials (AASHTO), 1st Edition, Washington, D.C.

Howard/Stein-Hudson Associates, Inc., (2010). *The Benefits of Retiming/Re-phasing Traffic Signals in the Back Bay*, Study prepared for Boston Transportation Department, Boston, MA.

Kesur*,* K. B. (2010). "Generating More Equitable Traffic Signal Timing Plans ", *Transportation Research Record*, Vol. 2192, 108-115.

Klunder, G., Abdoelbasier, A., Immers, B. (2006). "Development of a micro-simulation model to predict road traffic safety on intersections with surrogate safety measures", Paper (No. 1894) presented at ITS World Congress in London, UK.

Kosonen, I. and Ree, S. (2000). "*The potential for microscopic simulation in traffic safety and conflict studies*", Proceedings of Conference on Road safety on three continents, Pretoria.

Migletz, D. J., Glauz, W. D., and Bauer, K.M. (1985). "*Relationships Between Traffic Conflicts and Accidents"*, Report No. FHWA-RD-84-042, Federal Highway Administration, Washington, DC.

Moore, S.E., and Lowrie, P.R. (1976). "Further on the effect of coordinated traffic signal systems on traffic accidents." Proceedings of the 8th AARB Conference 8(5), Session 26, 10-15.

Mulandi, J., Stevanovic, A.Z., and Martin, P.T. (2010). "Cross-Evaluation of Signal Timing Optimized by Various Traffic Simulation and Signal Optimization Tools." *Transportation Research Record* 2192, 147-155.

Osyczka, A. 1985. "Multicriteria optimization for engineering design." In Design Optimization, J. S. Gero, Ed. Academic Press, Inc., New York, NY, 193–227.

Ozbay, K., Yang, H., Bartin, B., and Mudigonda, S. (2008). "Derivation and Validation of New Simulation-Based Surrogate Safety Measure", *Transportation Research Record: Journal of the Transportation Research Board*, 2083, 105-113.

Ozbay, K., Yang, H., Bartin, B., and Mudigonda, S. (2008). "Derivation and Validation of New Simulation-Based Surrogate Safety Measure", *Transportation Research Record: Journal of the Transportation Research Board*, 2083, 105-113.

Pareto, V. 1896. Cours D'Economie Politique. Rouge, Lausanne, Switzerland.

Perkins, D. and Harris, J. (1967). "Criteria for traffic conflict characteristics", Report GMF 632, General Motors Corp., Warren, MI.

Planung Transport Verkehr AG (2010). VISSIM 5.30 User Manual. Karlsruhe, Germany: PTV.

Sabra, Z.A., Gettman, D., Henry R.D., and Nallamothu, V. "*Balancing Safety and Capacity in an Adaptive Signal Control System - Phase 1*", Report No. HRT-10-038, Federal Highway Administration, Washington, DC, 2010.

Stevanovic, A., Martin, P.T., and Stevanovic, J. (2007). "VISGAOST: VISSIM-based Genetic Algorithm Optimization of Signal Timings", *Transportation Research Record: Journal of the Transportation Research Board*, 2035, 59-68.

Stevanovic, A.Z., Martin, P.T. (2008). "An Assessment of the Suitability of Microsimulation as a Tool for the Evaluation of Macroscopically Optimized Traffic Signal Timings." *Journal of Transportation Engineering* ASCE, 134(2), 59-67.

Stevanovic, J., Stevanovic, A., Martin, P.T., Bauer, T. (2008). "Stochastic optimization of traffic control and transit priority settings in VISSIM", *Transportation Research C*, 16(3), 332-349.

Stevanovic, A., Stevanovic, J., Zhang, K., and Batterman, S. (2009). "Optimizing Traffic Control to Reduce Fuel Consumption and Vehicular Emissions: Integrated Approach of VISSIM, CMEM, and VISGAOST", *Transportation Research Record: Journal of the Transportation Research Board*, 1707, 105-113.

Sun, D., R.F. Benekohal, and S.T. Waller (2003). "Multi-objective Traffic Signal Optimization Using Non-dominated Sorting Genetic Algorithm", *IEEE Intelligent Vehicles Symposium*, Piscataway, N.J., 198-203.

Tarko, A., G. Davis, N. Saunier, T. Sayed, and S. Washington. (2009). *Surrogate Measures of Safety*. White paper from Subcommittee on Surrogate Measures of Safety, Transportation Research Board of the National Academies, Washington, D.C.

Zegeer, C.V., and Deen, R. (1978). “Traffic Conflicts as a Diagnostic Tool in Highway Safety”, Transportation Research Record No. 667.

Zhou, M., and Sisiopiku, V. (1997). "Relationship Between Volume-to- Capacity Ratios and Accident Rates", *Transportation Research Record: Journal of the Transportation Research Board,* 1581, TRB, National Research Council, Washington, D.C., 47–52.

Zimmerman, K.H. and Bonneson, J.A. (2005). *In-Service Evaluation of a Detection-Control System for High-Speed Signalized Intersections*, Implementation Report No. 5-4022-01-1, Texas Transportation Institute, College Station, TX.