Multi-criteria analysis of optimal signal plans using microscopic traffic models

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Abstract

Increasing concerns on environment and natural resources, coupled with increasing demand for transport, put lots of pressure for improved efficiency and performance on transport systems worldwide. New technology nowadays enables fast innovation in transport, but it is the policy for deployment and operation with a systems perspective that often determines success. Smart traffic management has played important roles for continuous development of traffic systems especially in urban areas. There is, however, still lack of effort in current traffic management and planning practice prioritizing policy goals in environment and energy. This paper presents an application of a model-based framework to quantify environmental impacts and fuel efficiency of road traffic, and to evaluate optimal signal plans with respect not only to traffic mobility performance but also other important measures for sustainability. Microscopic traffic simulator is integrated with micro-scale emission model for estimation of emissions and fuel consumption at high resolution. A stochastic optimization engine is implemented to facilitate optimal signal planning for different policy goals, including delay, stop-and-goes, fuel economy etc. In order to enhance the validity of the modeling framework, both traffic and emission models are fine-tuned using data collected in a Chinese city. In addition, two microscopic traffic models are applied, and lead to consistent results for signal optimization. Two control schemes, fixed time and vehicle actuated, are optimized while multiple performance indexes are analyzed and compared for corresponding objectives. Solutions, representing compromise between different policies, are also obtained in the case study by optimizing an integrated performance index.

Key words: Optimal signal planning, stochastic optimization, environmental impacts, energy efficiency, microscopic traffic simulation, emission model.

1. Introduction

The rapid increase of transport requirements has brought challenges to sustainable development of our society with respects to emissions and energy consumption induced by traffic. Current road transport produces about one fourth of principal greenhouse gases, considered to be the major factor of global climate change. Despite significant improvement in engine and fuel technology, road vehicles continue to be the main source of local pollutant emissions in urban areas including carbon monoxide (CO), nitrogen oxides (NO_x), hydrocarbon (HC) etc. Increased knowledge has been obtained on how these emissions may deteriorate human health and social welfare. It becomes, therefore, important for planers to be able to quantify the environmental impacts of road traffic during the planning and management of transportation system.

The advances in computer power and software tools have promoted links of traffic models with energy and emission models in evaluation of traffic impacts (Boulter and McCrae, 2007). Depending on the traffic and emission models adopted, the integration can be carried out at different resolutions, which make it feasible to evaluate performance indexes in sustainability and adapt traffic management policies. The approach has been applied from improvement of

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traffic flow (Roland and Quddus, 2006) to local traffic measures (e.g. Panis et al., 2006). While the method seems to be clear and promising due to current model development, there is still lack of more comprehensive studies that may guide and promote sustainable traffic management in planning practice. The recent crisis of air quality deterioration in cities e.g. in China and other fast developing countries, partly due to traffic pollution, makes the study on policy measures for ecological transport even more important and urgent.

This work will mainly focus on, through a detailed case study, evaluation of optimal signal planning concerning environmental impacts and energy efficiency. The rest part of this section will first give a short overview of signal planning and emission modeling approaches. The research objective of the study will then be presented explicitly.

1.1. Traffic signal planning

Signalized intersections are an essential instrument of road traffic control, which supports sharing right of ways among vehicles and other users. There are mainly three types of signal control schemes for isolated intersections: fixed time control (FT), vehicle actuated control (VA) and adaptive control (AS). Signal timings in FT control are usually estimated based on traffic data collected and kept constant in the logic. While it may show good performance in normal traffic conditions, the scheme sometimes fails to deal with dynamic traffic conditions. The VA control improves over the FT control by using online vehicle detectors. By extending green time of a particular stage according to detected traffic at approaches, real-time traffic is counted in the control logic. A well-formed VA control can significantly reduce travel delay and improve fuel efficiency (Courage et al., 1996). However, the green extension is only based on vehicle detection at stretches in green. The AS controller adapts signal plans based on vehicle detections on both running and queuing approaches. Signal plan can be more efficient when several intersections are coordinated (Gartner et al., 1975).

Optimal signal planning was first proposed in the late 1950s when Webster (1958) introduced a mathematical model to minimize travel delay at intersection. Research interest has since then been focused on more advanced control schemes and sophisticated detector layout (e.g. Bång and Nilsson, 1976). The emergence of computer traffic model has fostered the study on optimal signal control and application. Appearance of commercial tools like TRANSYT promoted direct application of optimal signal settings in reality. The research interest in signal optimization is forwarded to more advanced optimization for complex controllers and different objectives. For example, Park and Kamarajugadda (2007) proposed the application of genetic algorithms (GA) with detailed traffic models in optimizing signal parameters. Meanwhile, recent attention has been put on environmentally friendly traffic signal planning (e.g. Park et al., 2009). In particular, Stevanovic et al. (2009) evaluated optimal signal settings for an AS controller, called SCOOT, by integrating the VISSIM traffic microscopic model with a vehicular emission model, CMEM. A GA-based program was implemented to search optimal signal parameters. Several policy measures for signal planning were assessed by a case study on a road network in the United States.

1.2. Emission estimation models

Emission models have been developed to estimate the levels of vehicle exhaust emissions (CO_x, NO_x, HC etc.) and fuel consumption. They can generally be classified into aggregate models and microscopic models. Aggregate models are mostly used for planning and evaluation of environmental impacts of traffic system, with static approaches estimating total or average traffic emission and fuel consumption. The models require macroscopic input data such as average traffic speed on road links, total vehicle travel distance etc. For example, ARTEMIS (Keller and Kljun, 2007) and MOVES (Vallamsundar and Lin, 2011) (different resolutions) have been used as aggregate emission models for many transportation applications in the EU and US respectively.

Microscopic emission models become widely applied thanks to their capability of assessing traffic impacts in operational transportation projects prior to field implementation. The most important aspect is that they can be used, in a consistent accuracy, together with microscopic traffic models in evaluation and management of local traffic through dynamic operations. Such models can be even further classified into statistical-based and modal-based models. Statistical micro-scale models predict instantaneous emission rates by including in regression equations, functions of speed, acceleration, their product and dummy variables for driving modes, e.g. VT-Micro developed by Rakha et al. (2004). Modal micro-scale models consider the modal operation of a vehicle, and are based on detailed physical analysis of emission production to predict instantaneous emissions, as a function of driving modes, e.g. CMEM (Scora and Barth, 2006). Detailed information on vehicle state and emission is therefore required to determine model forms and to estimate model parameters (Rapone et al., 2008).

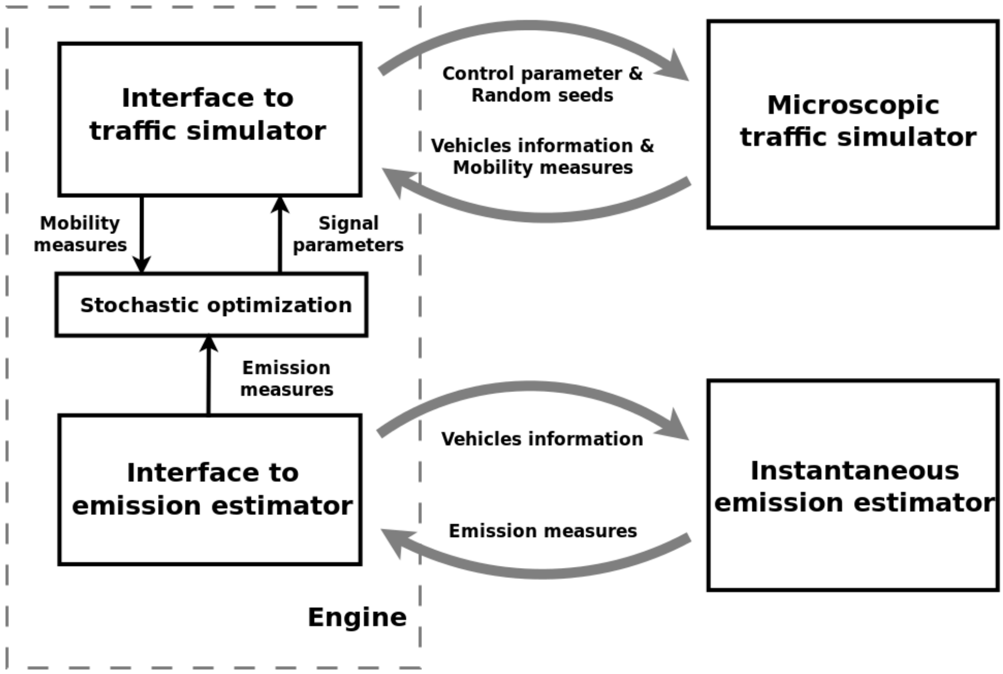

Fig. 1. An integrated computational framework for traffic signal optimization.

1.3. Research objectives

One main objective of this study was to demonstrate, through a detailed case study in a Chinese city, the essential procedures to implement signal optimization based on traffic simulation, while evaluating environmental impacts of optimal signal plans generated. Technically, the project intends to develop, based on the third party traffic and emission simulators, an efficient computational framework capable to analyze signal plans for different policy goals or objectives in practice. While evolutionary based optimization with integrated traffic and emission models was reported to be able of generating signal plans fulfilling objectives in both mobility and sustainability, there is still few application of the approach in planning practice. In addition, more robust knowledge on the impact of policy goals is desired, especially concerning environmental impact, energy efficiency and their interaction with mobility measure. This paper has therefore another focus to assess the policy impact of the objectives in sustainability using the integrated modeling framework.

2. Methodology

2.1. Overview of the framework

A computational engine is developed to integrate traffic and emission models while applying stochastic optimization algorithms to assess various signal control policies. Although similar approach has been applied in literature, this study establishes a general software framework so that multiple traffic and emission models can be incorporated, and the result of analysis can be compared. Figure 1 illustrates the abstract framework for such an integration. The core engine program is designed to have a standard interface able of running traffic simulation model using different control parameters. Multiple simulation runs are automated with different random seeds, required for statistically significant evaluation. The engine has the capacity to call emission estimator, through an interface, by providing second-by-second inputs of dynamic vehicles information or average traffic statistics obtained during traffic simulation.

When developing optimal signal plans, it is common to have an objective being a function of the control parameters and other inputs to traffic system such as traffic demand, composition, driver behavior parameters etc. Conventionally, the control objective is only formulated to represent mobility, or efficiency, of traffic system e.g. total or average travel or queue delay. When environmental impacts are considered in active traffic management, more complicated objective functions are introduced by using other surrogate measures like emissions, energy consumption and even integrated objective (Li et al., 2004). The modeling framework is therefore able to evaluate not only mobility but also other measures such as emission and energy consumption.

Since both microscopic traffic and emission models are in the form of the third-party software, the GA heuristic is applied to search global optimal solution. A normal single-objective GA algorithm is implemented, which can simultaneously search best signal parameters, such as cycle length, green times etc., through selection, crossover and mutation operations (Spall, 2003). But different GA operators are also explored in this work to enhance the optimization performance.

As reported by previous work, the optimization is often limited by computing resource due to large computational requirements. Therefore, distributed computing approach is often applied with the idea to allocate the computational intensive tasks to different CPUs or computers. In this application, both traffic and emission simulations are computationally expensive procedures. So the application has the capacity to allocate multiple traffic simulation runs to different processes (depending on the support of traffic simulators) while the emission calculation can be even distributed to other machines (Ma et al., 2014). In that case, vehicle states generated in traffic simulation are sent to emission calculation software for detailed emission estimation.

2.2. Microscopic traffic models

Microscopic traffic models describe complex traffic system through stochastic simulation of individual vehicle movements and state evolution of other traffic objects. They represent detailed behavior of and interaction among different objects, such as driver reaction to other vehicles, traffic signal, pedestrians, and other perceived surroundings. Two popular traffic simulation tools, VISSIM and SUMO, are integrated in the computational framework.

VISSIM is a popular discrete-time based microscopic model developed by PTV (2009). It simulates traffic flow by moving driver-vehicle-units (DVU) across road network. The traffic dynamics in VISSIM is mainly determined by its longitudinal psycho-physical car-following model and latitudinal rule-based lane-changing model. VISSIM has been extensively used in transport planning and management by not only researchers but also traffic planers and other practitioners. SUMO is a relatively new and open-source traffic simulation tool, with highly portable and microscopic properties. It has been continuously developed and maintained by the German Aerospace Center (Krajzewicz et al., 2012). SUMO has a suite of applications including various functions for preparing simulation scenarios, including network generations, demand generations etc. Flow dynamics in SUMO is similarly based on lane desired speed distribution and parameters in acceleration and car-following (Krauß, 1998).

Calibration of the models is important for effective simulation. In the microscopic case, tuning driver behavior models including car-following and lane-changing models is essential to the simulation fidelity. A valid approach for behavioral modeling is to develop model structure and estimate model parameters based on detailed driver behavior data collected from reality. However, it is, in practice, more convenient and feasible to calibrate models using aggregate traffic flow data (e.g. Toledo et al., 2004). Therefore, driver behavior parameters in VISSIM are first adjusted using collected traffic data in this study. For the sake of consistency between two simulators, car-following parameters in SUMO is then tuned based on the simulation result in VISSIM.

Traffic data

This study aims to calibrate main behavior parameters in VISSIM using on-spot traffic data collected near a large intersection in Wuhan, where the performance for optimal signal control is later analyzed. To emulate real traffic conditions, traffic data was collected during 15:00-17:00 on May 20^{th}, 2010. Figure 2 shows that four cameras were installed at the stop lines to observe acceleration behavior and turning. Four additional cameras were mounted at the entry stretches (100-150 meters from the stop lines) to measure traffic flow rate and speed at each station. A self-developed program facilitates the derivation of traffic flow rate and vehicle speed at the observing stations by video analysis. Since the detailed control logic is not available, real signal timings are observed at the intersection and later approximated by a FT controller.

Model tuning procedures

In order to create models simulating real traffic with high fidelity, the following procedures illustrate how the behavioral parameters in VISSIM are tuned using aggregated traffic flow data:

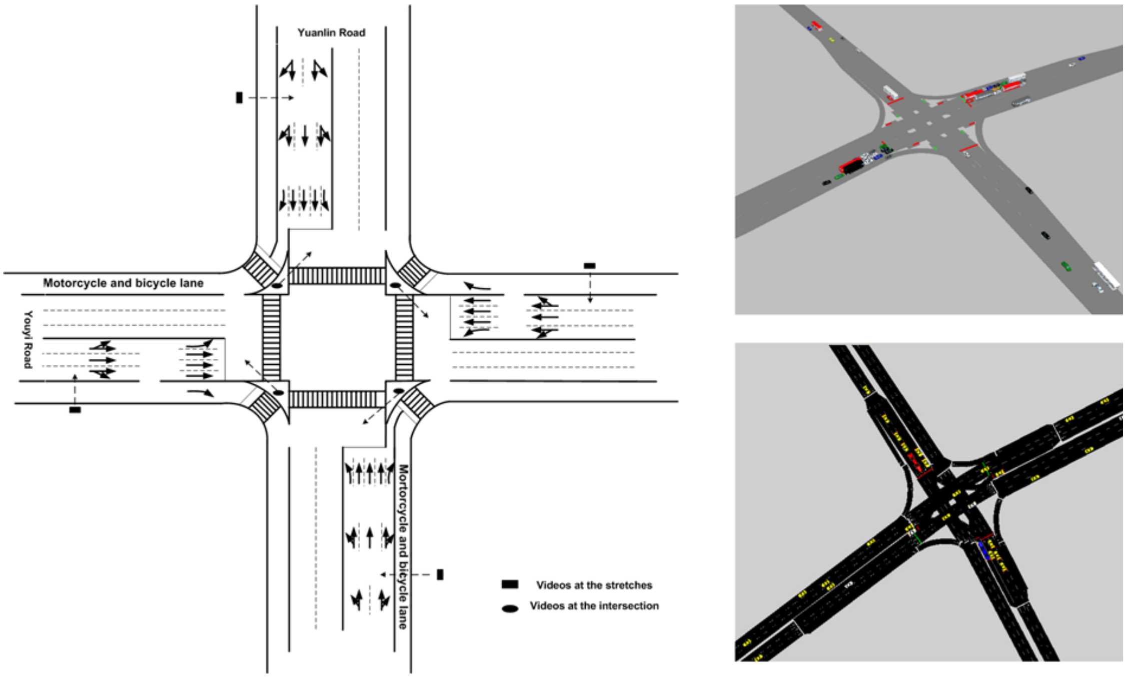

Fig. 2. Layout of the Wuhan intersection and its simulation models in VISSIM 3D (upper) and SUMO (lower).

- *Build the microscopic simulation network model in VISSIM;*
- *Select detailed statistical measure for model tuning:* average flow speed of each lane at the four stretches were used as the calibration reference; the objective is formulated by

$$\mathcal{L}(\overline{v}_{sim}, \overline{v}_{obs}, \boldsymbol{\beta}) = \Sigma_{k=1}^{4} \omega_k \Sigma_i \Big\{ (\overline{v}_{sim}(k, i, \boldsymbol{\beta}) - \overline{v}_{obs}(k, i)) / \overline{v}_{obs}(k, i) \Big\}^2 \tag{1}$$

  where $\overline{v}_{sim}$ and $\overline{v}_{obs}$ represent simulated and observed average traffic speed for lane i at the corresponding observing station k; ω_k represents the weights given to the observation station k and they can be treated as a reliability value assigned to measurements e.g. the inverse of data variance can be used; $\boldsymbol{\beta}$ is a vector of model parameters to be calibrated;

- *Select relevant behavioral parameters in VISSIM with reasonable value ranges:* this study selects behavioral parameters for calibration (see Table 1) according to the VISSIM manual; as lane-changing parameters have complex effects on simulation, longitudinal behavioral parameters are mainly calibrated within a predetermined range;
- *Automated parameter search:* a simple grid search was carried out within the parameter range; ten replications of traffic simulation are conducted to estimate the average traffic measures at those stations;
- *Evaluation of the model performance in VISSIM:* the improvement of the model parameters is evaluated using traffic counts obtained at the same stations.

After calibration of VISSIM, the following steps are then carried out to tune the SUMO model based on the simulation outputs from VISSIM:

- *Convert the VISSIM network for SUMO:* this conversion is conducted using two SUMO functions, NETCONVERT and VISSIM_PARSEROUTES;

Table 1
Behavior parameters selected for calibration and estimated results.

Behavior parameters	Valid range	Default values	Estimated values
Maximal look-ahead distance (m)	200 – 300	250	208
Maximal look-back distance (m)	100 – 200	150	137
Observed vehicle number	2.0 – 5.0	4.0	3.0
Average standstill distance (m)	0.5 – 5.0	2.0	0.6
Additive part of safety distance (m)	1.0 – 5.0	2.0	1.8
Multiple part of safety distance (m)	1.0 – 6.0	3.0	2.0
Max. deceleration for NCL* (m/s^2)	2.0 – 5.0	4.0	4.2

* NCL means necessary lane changing (NLC).

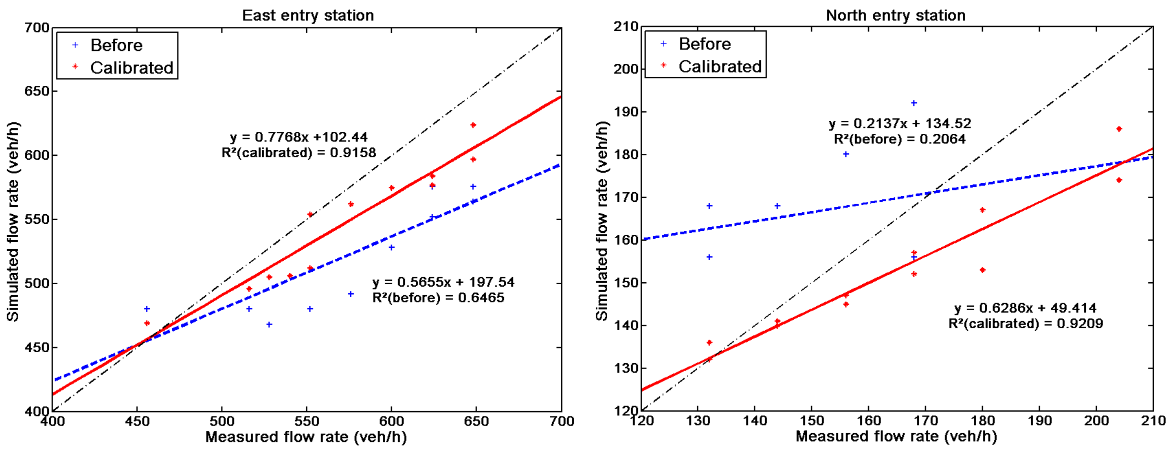

Fig. 3. Evaluation of VISSIM by comparison of simulated and measured traffic flow rates (at east and north entry stations).

- *Sensitivity test and adaption of SUMO:* vehicle speed distribution at a certain location (around 100 meters before stop line) for each direction is used as measure for testing and calibration. Speed distributions outputted from VISSIM are regarded as reference values. The paramters of desired speed and maximum acceleration are calibrated, while the following statistic is used to justify the difference between the speed distributions:

$$\chi^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i} \tag{2}$$

  where o_i and e_i represent speed frequencies at the interval i output from SUMO and VISSIM respectively;

- *Evaluation of the SUMO simulation:* travel time distribution of vehicles traversing the network are evaluated according to their origin and destination.

Calibration result

Table 1 summarizes the adaption of the selected parameters in VISSIM and the corresponding search range. The results show that parameters, capturing observed traffic patterns in Wuhan, are different from the default ones, which might describes behavior in Europe. This is understandable since driver behavior is related to many local effectors such traffic rules, social norms, culture etc. The estimated parameters are further validated according to average traffic flow rates based on 30 simulation replications, each of which adopts a random seed and runs a simulation of 2 hours. Figure 3 shows a comparison of the simulated and measured traffic flow rates at different locations. The calibration procedure improves the prediction on average flow rates i.e. simulated result after calibration is closer to observation.

Table 2
Calibrated desired speed in SUMO for different vehicle types.

Vehicle type	Desired speed * (m/sec)			
	West entry	East entry	North entry	South entry
LDV4	18.20	12.60	11.15	9.86
LDV6	17.60	12.60	11.15	9.86
Medium	14.20	14.72	10.60	9.00
Bus	11.80	11.80	8.02	7.82
HGV	13.80	14.72	10.50	9.40

* The default desired speed is 20 m/sec.

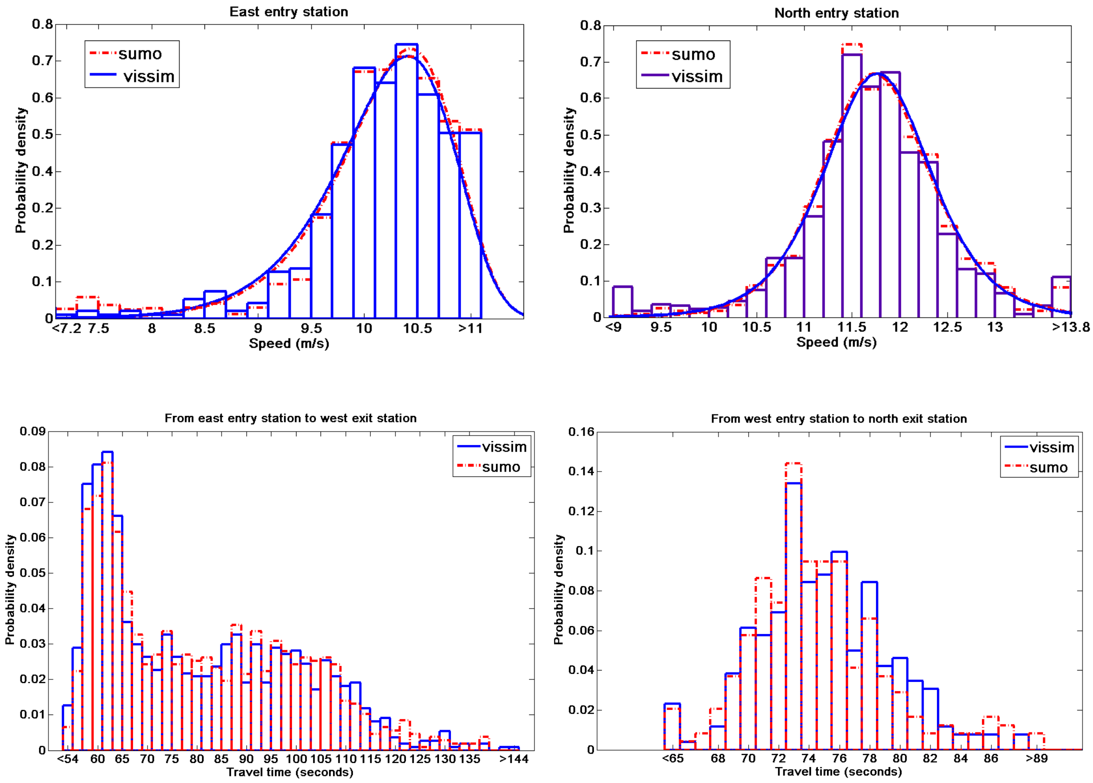

Fig. 4. SUMO calibration result on speed and travel time distributions.

Nevertheless, the calibration process is limited by the available data whereas the methodology can be improved if, for example, detailed vehicle trajectory data can be captured.

On the other hand, when default parameters in SUMO are used, the simulation results are quite different from the output from the VISSIM model already calibrated. Therefore, using speed distributions simulated by VISSIM as reference, the behavioral and desired speed parameters in SUMO are finely tuned. Table 2 summarizes the calibrated desire speed in SUMO, shown speed distributions not significantly different from VISSIM (Figure 4). In addition to speed distribution at the stretches, the travel time distributions, between selected entries and exits, are also compared for VISSIM and SUMO. By statistical test, the hypothesis that they fulfill the same distribution cannot be rejected.

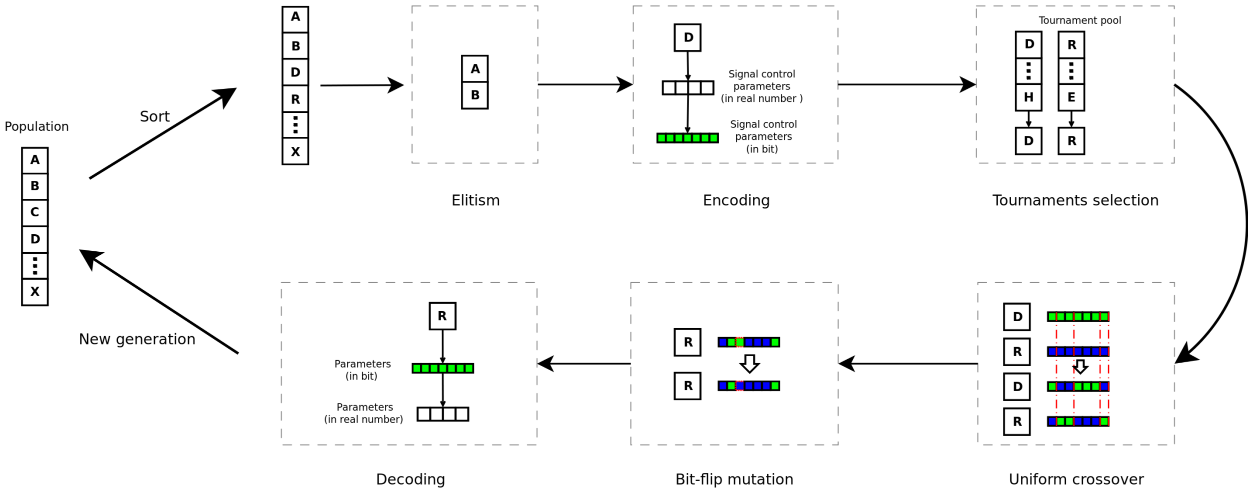

Fig. 5. Detailed procedures in the GA implementation.

2.3. Emission estimator

In order to quantify vehicular emissions accurately, an instantaneous emission model, CMEM, is used for traffic impact analysis in this study. CMEM is a load-based micro-scale model developed at UC, Riverside using chassis dynamometer data collected from 300 automobiles and light trucks of 26 vehicle categories (Scora and Barth, 2006). The model calculates second by second tailpipe emissions as a product of three parameters: fuel rate (r_{fuel}), engine-out emission index ($i_{em/fuel}$) and catalyst pass fraction (C_{pass}), that is

$$e_{tailpipe} = r_{fuel} \cdot i_{em/fuel} \cdot C_{pass} \tag{3}$$

These parameters are further modeled by decomposing the emission generation process into modules corresponding to physical phenomena: engine power, engine speed, air-to-fuel rate, fuel use, engine-out emission, and catalyst pass fraction. Emission levels under stoichiometric, cold-start, enrichment, and enleanment conditions are identified differently. Since the model estimates vehicular emissions in the United States, both fuel-related parameters (e.g. ε_1, K_0, and P_{scale}) and emission-related parameters (e.g. α_{HC}, b_{HC}, α_{CO}, b_{CO}, α_{NO_1}, and b_{NO}) are finely tuned based on portable emission measurement in Wuhan in a previous study (Ma et al., 2012). The identified model is thereafter applied for emission prediction in signal planning.

2.4. GA-based signal optimization

Genetic algorithm is a widely used evolutionary algorithm for solving optimization problems in many engineering fields (Spall, 2003). This heuristic optimizer starts from a population of feasible solutions, randomly generated at the beginning, and moves towards the global optimum through population evolution justified by chromosome fitness. To create a new population, GA performs the following steps: elitist keeping, encoding, selection, crossover, mutation and decoding.

Figure 5 summarizes the procedure with the GA operators being empirically chosen for our signal optimization. An operator evaluation procedure will be expained in the case study. Elitism allows the "best" chromosomes, or genes, from current population to carry over to the next population without being altered. The encoding function converts signal parameters from integer to a string of bits (0 or 1). The parameter range is therefore identified by the bit length.

A tournament selection process stochastically identifies parents with "good" genes and then conduct crossover through a fitness-driven process. This algorithm involves running several tournaments among a few individuals, which are chosen at random from the population. Winner of each tournament (the one with the best fitness value) is then selected. Uniform crossover is one of the mating operators to produce new population. Two selected parents are involved in one crossover process. Bits at the same position are possible to be swapped between these two chromosomes with a fixed crossover probability. Bit-flip mutation inverts bit values (if the bit value is 1, it is changed

Table 3
Notation for the mathematical formulation in signal optimization.

Parameters	Notations
$P(\mathbf{x}, \boldsymbol{\phi}, \mathbf{r})$	objective function according to the policy goals
$\mathbf{x}$	a vector of other inputs to traffic model such as demand and traffic composition
$\mathbf{r}$	a set of random seeds
C	cycle length (sec) at the intersection
C_+	maximum cycle length at the intersection
C_-	minimum cycle length at the intersection
S	total stage number
y_s	duration of the yellow time for stage s
I_s	red time between the end of green time for stage s and the start of the next green time
$\boldsymbol{\psi}$	a vector of green times for different stages in FT control
ψ_s	duration of the green time for stage s for FT control
$\psi_{s,-}$	minimum acceptable duration of green time for stage s
$\psi_{s,+}$	maximum acceptable duration of green time for stage s
$\boldsymbol{\phi}$	a vector of green time bounds for VA control
$\phi_{s,l}$	lower bound of green time for stage s for VA control
$\phi_{s,u}$	upper bound of green time for stage s for VA control
$\phi_{s,l-}$	minimum acceptable lower bound of green time for stage s
$\phi_{s,l+}$	maximum acceptable lower bound of green time for stage s
$\phi_{s,u-}$	minimum acceptable upper bound of green time for stage s
$\phi_{s,u+}$	maximum acceptable upper bound of green time for stage s

to 0 and vice versa) in a chromosome with a fixed mutation probability. Decoding is the opposite process of encoding, which converts signal parameters from bits to integer, interpreted as signal timing parameters.

Generally, there are two crucial aspects that justify GA performance: one is the convergence ability and the other is capacity to carry out global search. Convergence performance requires testing different genetic algorithm operators for the specific problem. In terms of global searching, Srinivas (1994) demonstrated that values of crossover probability and mutation probability play significant roles on search space. Usually, the higher the mutation probability is the bigger area is covered by the search space. In order to achieve better performance by global search in our platform, adaptive mutation probability is introduced to enhance the GA performance i.e.

$$p_{mutation} = \begin{cases} (p_{max} - p_{min}) \times \dfrac{f_{max} - f}{f_{max} - \overline{f}} + p_{min} & f \geq \overline{f} \\ p & f < \overline{f} \end{cases} \tag{4}$$

where $p_{mutation}$ represents the mutation probability of the solution; f, f_{max},$\overline{f}$ represent fitness value of solution, the maximum and average fitness values respectively; p_{max} and p_{min} are the maximum and minimum mutation probabilities; p is a constant mutation rate. The adaptive mutation scheme increases the spread of the search space, and hence improves the GA performance.

3. Case study

3.1. Optimization formulation

The case study analyzes optimal signal plan using the intersection model that was calibrated in the previous section for two different traffic simulators. Real signal timing was observed and then approximated by a FT controller that is used as a baseline case. The computational framework proposed is therefore applied to implement policy goals for signal control. For FT control, the optimization problem can then be formulated as follows:

$$
\begin{aligned}
& \min_{\boldsymbol{\psi}} P(\mathbf{x}, \boldsymbol{\psi}, \mathbf{r}) \\
\text{s.t.} \quad & C_- \le C \le C_+ \\
& C = \Sigma_{s=1}^{S} \psi_s + \Sigma_{s=1}^{S} I_s + \Sigma_{s=1}^{S} y_s \\
& \psi_{s,-} \le \psi_s \le \psi_{s,+}.
\end{aligned} \tag{5}
$$

The variables used in the optimization are explained in Table 3. A fixed stage vehicle actuated (VA) signal control is also optimized for policy analysis. In contrast with searching green time value for each fixed stage, the VA control logic decides green time extension or stage termination based on detected vehicle gaps in the current stage. The green extension time is recommended as a fixed value, related to minimum allowable gap depending on detector allocation. In our case, all detectors are allocated near stop line, and so a 3 second green extension time is therefore applied. The minimum and maximum green times for each stage are the values to be optimized. Therefore, the VA control has more parameters and the problem is formulated as follows:

$$
\begin{aligned}
& \min_{\boldsymbol{\phi}} P(\mathbf{x}, \boldsymbol{\phi}, \mathbf{r}) \\
\text{s.t.} \quad & C = \Sigma_{s=1}^{S} \phi_s + \Sigma_{s=1}^{S} I_s + \Sigma_{s=1}^{S} y_s \\
& \phi_{s,l} \le \phi_s \le \phi_{s,u} \\
& \phi_{s,l-} \le \phi_{s,l} \le \phi_{s,l+} \\
& \phi_{s,u-} \le \phi_{s,u} \le \phi_{s,u+}.
\end{aligned} \tag{6}
$$

In order to analyze different policies in traffic signal control, the objective function is set by using individual measures on mobility, energy efficiency and environmental impacts. In addition, an integrated performance index (PI), standing for a compromise for different objectives (Li et al., 2004), is also optimized and analyzed in the study i.e.

$$
PI = \sigma_d \frac{d}{d_0} + \sigma_f \frac{f}{f_0} + \sigma_e \frac{e}{e_0} \tag{7}
$$

where d, f and e represent average travel delay, total fuel consumption, total emissions (including CO, HC and NOx) respectively; d_0,f_0 and e_0 are the corresponding values in the baseline case; σ_d, σ_f, and σ_e are policy weights describing the relative importance of these measures.

3.2. Simulation implementation

The intersection models being calibrated in section 2.2 are used for evaluation of optimal signal plans. Figure 2 shows that the intersection has four arms in the approaching directions, each of which has five lanes (including three straight through and one left-turn before stop line). Like many other Chinese cities, the right-turn has a separate lane, not regulated by signal control. FT signal parameters are observed from field data and approximated by a green time sequence of 18, 75, 15, and 15 seconds at each stage while amber time is set as 3 seconds equally. An interval of red time 2 seconds is added before stage transition for clearance of vehicles.

The case study will optimize FT and VA controllers using the same phase sequence. They both will be compared with the baseline case concerning multiple criteria. The fixed time plan can be easily implemented using microscopic simulator whereas VA signal control logic has to be coded in simulation. Vehicle actuated programming (VAP) is a tool in VISSIM that facilitates the implementation of VA control logic. In SUMO, signal control logic is implemented using the Python language, while the simulation engine calls the signal function via the TraCI server, a communication interface.

An essential challenge in the implementation is the computational requirements since microscopic traffic simulation and instantaneous emission estimation (also the IO operations in CMEM) are both computationally expensive procedures. Meanwhile, simulation replications with different random seeds are also important to make statistically reliable evaluation of all objective functions. To achieve a compromise between computational cost and statistical requirement, twenty random seeds are used in the fitness evaluation in GA optimization. In addition, the tool developed

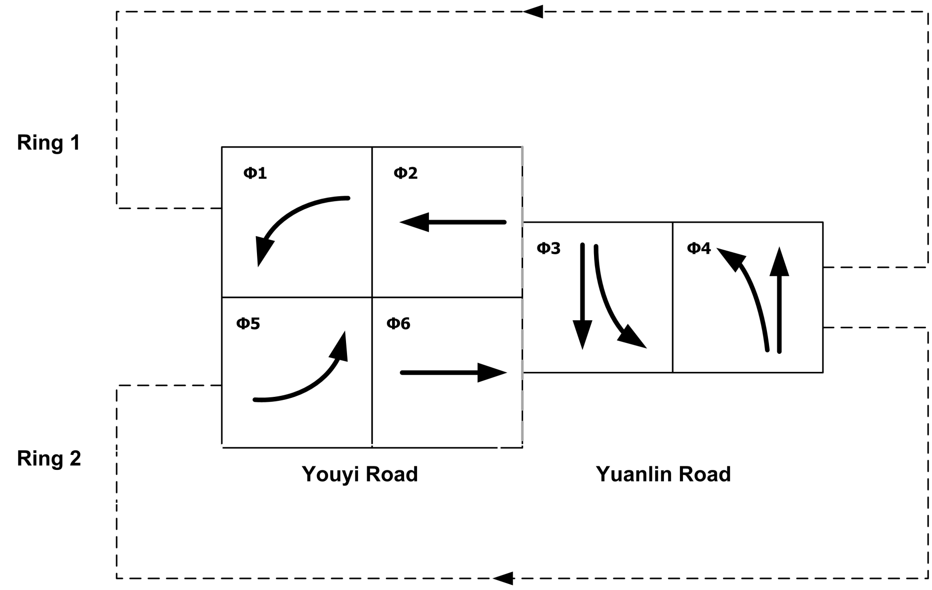

Fig. 6. The phase rings for signal control at the intersection.

in the study accelerates the optimization process by directly calling simulator interfaces for multiple simulation runs. Parallel computing approach is introduced to carry out multiple simulation runs simultaneously when the SUMO simulator is used. All numerical experiments were conducted on a Windows server with two Xeon 2.40GHz duel-core processors and 8GB memory. The GA optimization using parallelized SUMO simulation runs performs much faster.

3.3. GA operator test

As mentioned in section 2.4, appropriate GA operators in selection, crossover and mutation could lead to improved optimization performance. Therefore, four sets of commonly used GA operators are evaluated for best convergence performance in Table 4. The final operator set, using tournament selection, uniform crossover, and bit-flip mutation, shows the most efficient combination illustrated in Figure 7. In summary, the following GA operators and corresponding parameters are adopted for stochastic optimization:

- The population size is set to 20;
- The evolution generation is set to 60;
- Elite number is 2;
- The tournament pool size is 4;
- The probability for uniform crossover is 0.50;
- The maximum mutation probability is 0.50 whereas minimum is 0.05.

3.4. Policy evaluation for optimal signal plans

Computational experiment was carried out to assess the performance of signal plans in terms of mobility and sustainability when different policy goals are applied. The optimal signal parameters, obtained for different objectives, are then applied to evaluate performance measures in travel delay, fuel efficiency and emission impacts derived from simulation results of 30 runs. It was found that almost all the optimal signal plans lead to better performance, in terms of mobility and sustainability, when compared to the baseline case. Table 5 and 6 summarize all performance measures for FT controller obtained from VISSIM and SUMO when each policy measure is optimized.

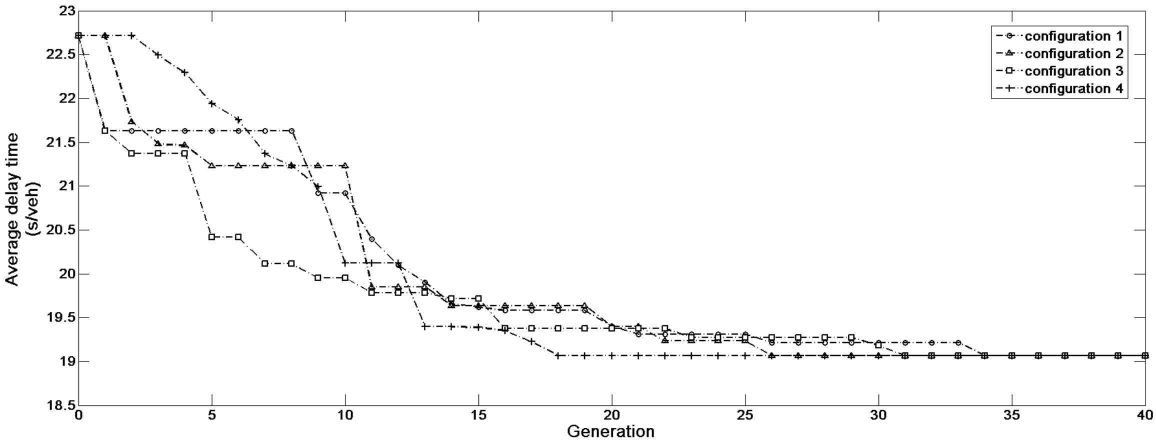

Fig. 7. Convergence performance of GA using different operator sets.

Table 4
Comparison of different scenarios of GA operators.

Combination	Selection	Crossover	Mutation	Number of generations
1	Roulette wheel	Two-point	Bit-flip	40
2	Roulette wheel	Uniform	Bit-flip	40
3	Normal geometry	Uniform	Bit-flip	40
4	Tournament	Uniform	Bit-flip	40

Normally, if a signal plan leads to traffic jam, average travel delay (for all vehicles) would be increased significantly. Therefore, when average delay is used as the policy goal or objective, poor traffic conditions could be detected, and such signal plans will be discarded during GA optimization. When comparing results corresponding to minimum total fuel consumption and optimal average travel delay (row 6 and 2 in table 5 and 6), total fuel consumption is 1.88% higher when average travel delay is minimized. However, when total fuel consumption is set as the policy goal, average travel delay is 14.44% higher. This accords with the results in literature (Courage and Parapar, 1975), showing that there is an obvious trade-off between travel delay and fuel consumption in the signal optimization problem. In addition, poor traffic conditions might not be recognized when total fuel consumption is considered as an objective function. This can be explained from the following perspective: when traffic is congested and vehicles stop more, often being idling, fuel consumption is therefore less than the situation where vehicles keep running at a certain speed. As a result, if total fuel consumption is minimized, traffic jam is possible to be perceived as a favorable outcome.

The result on performance measures also shows that average travel delay and total number of stops are non-commensurable. This is in accordance with the previous findings (e.g. Sun et al., 2003), where improvement of total stop number usually corresponds to deterioration in travel delay measure. This indicates that solution by minimizing total number of stops may result in more traffic congestions. When there is more congestion in traffic, number of stops may be reported less in a time interval since vehicle drives less and hence stops less frequently. Therefore, both total fuel consumption and total stop number are not effective objectives concerning the ability to improve traffic conditions.

When average fuel consumption (or fuel economy in g/km) is set as the optimization objective, optimal signal timings bring about lower delay, about 4% reduction, than the case if total fuel consumption is applied as our policy goal. A similar situation occurs with stop-related measures. When average number of stops (vehicle stops per kilometer) is regarded as the goal, optimal signal plan reports less average travel delay compared with the case that total stop number is the minimization objective. The numerical result using policy goals in stop number and fuel consumption per unit distance (i.e. per km) indicates that they could be more effective individual measures for detecting poor traffic

Table 5
Results of policy evaluation for FT controller using VISSIM.

Objectives	Performances measures					
	Avg. delay (sec/veh)	Avg. stops (veh/km)	Total stops (veh/h)	Avg. fuel (g/km)	Total fuel (kg/h)	Integrated PI
Baseline	24.540	0.495	1,783.84	75.250	270.987	1.000
Avg. delay	19.801	0.506	1,825.60*	73.851*	266.279*	0.909
Avg. stops	21.866	0.454	1,696.40	72.968	263.573	0.920
Total stops	22.823	0.465	1,636.03	73.416	262.750	0.938
Avg. fuel	22.168	0.460	1,715.01	72.698	263.445	0.925
Total fuel	23.143	0.469	1,678.73	73.376	261.274	0.946
Integrated PI	20.399	0.486	1,768.87*	73.134	264.003	0.904

* Statistically not significantly different from the baseline case at the 5% level.

Table 6
Results of policy evaluation for FT controller using SUMO.

Objectives	Performances measures					
	Avg. delay (sec/veh)	Avg. stops (veh/km)	Total stops (veh/h)	Avg. fuel (g/km)	Total fuel (kg/h)	Integrated PI
Baseline	25.441	0.480	1,715.93	74.159	262.181	1.000
Avg. delay	20.931	0.485	1,778.50*	72.948 *	259.337*	0.918
Avg. stops	22.090	0.456	1,653.11	71.299	255.982	0.936
Total stops	23.037	0.470	1,584.08	72.638	253.859	0.952
Avg. fuel	22.262	0.463	1,701.17*	71.112	255.666	0.937
Total fuel	23.486	0.475	1,625.10	72.115	253.087	0.953
Integrated PI	21.073	0.477	1,707.93*	71.819	256.023	0.915

* Statistically not significantly different from the baseline case at the 5% level.

conditions than vehicle stops and fuel consumed per unit time (e.g. per hour). Nevertheless, fuel-delay and stop-delay trade-offs are in any case still noticeable. For example, delay value when minimizing average fuel consumption still leads to 10% more travel delay than when average travel delay is minimized.

When comparing the performance measures of the signal plan resulting in optimal average number of stops to the case that fuel economy is minimized, the addition in fuel consumption is insignificant (0.37%). Similarly, difference in average number of stops are quite small (1.30%) between the two optimal signal plans. This indicates that the goal in average stop number is, to a certain degree, in accordance with fuel economy in this single intersection case.

From the analyses above, it is hard to argue that the signal plans minimizing fuel consumption should be implemented because they have clear negative influence on the mobility measure. But it is also difficult to ignore the potential benefits in energy, and even emissions, especially when energy- and environment-oriented policies gain increasing attention worldwide. Therefore, signal plan, minimizing an integrated performance index proposed in literature (Li et al., 2004), is applied and evaluated as a compromising policy goal in practice, as the objectives in both mobility and sustainability are taken into account (i.e. 40% average delay, 30% fuel consumption and 30% emission). For example, when comparing the case that integrated PI is optimized with the scenarios of minimized total fuel consumption, significant reduction in average travel delay (around 12%) is obtained with a small loss in fuel (1.2%) is obtained. This reflects a relatively positive return by policy integration.

The environment-oriented criteria are also compared in our case study. Table 7 shows that all optimal FT signal plans lead to fewer total emissions than the baseline case. The smallest value of total emissions is found when average number of stops is applied as the policy goal. This indicates that the total emission value has a direct correlation with vehicle stops. Besides, similar patterns are observed when comparing total fuel consumption and total emissions. Especially, total emissions follow a similar trend as fuel consumption goes up and down in different scenarios. However, higher percentage of reduction in total emission, than fuel saving, is always obtained in comparison to the baseline case. For example, reduction in total emissions reaches 8% whereas the corresponding saving in total fuel consumption is only 3% when average fuel consumption is used as the policy goal. Among these three types of emissions, the

Table 7
Emission results for optimized FT signal plans under different policy goals.

Objectives	Total CO (kg/h)	Total HC (kg/h)	Total NO_x (kg/h)	Total emissions (kg/h)
Baseline	36.581	1.258	2.007	39.965
Avg. delay	35.685*	1.251*	2.002*	38.939*
Avg. stops	33.190	1.169	1.961*	36.420
Avg. fuel	33.079	1.162	1.992*	36.443
Integrated PI	34.230	1.221	1.986*	37.439

* Statistically not significantly different from the baseline case at the 5% level.

Table 8
Comparison of the results from VISSIM and SUMO with optimized FT signal plans.

Performance measures	Optimal objectives					
	Avg. delay		Avg. fuel		Integrated PI	
	VISSIM	SUMO	VISSIM	SUMO	VISSIM	SUMO
Avg. delay (sec/veh)	19.801	20.931	22.168	22.262	20.399	21.073
Avg. fuel (g/km)	73.851	72.948	72.698	71.112	73.134	71.819
Total CO (kg/h)	35.685*	34.290*	33.079	32.503	34.230	33.737
Total HC (kg/h)	1.251*	1.189*	1.162	1.132	1.221	1.184
Total NO_x (kg/h)	2.002*	1.916*	1.992*	1.931*	1.986*	1.953*
Total emissions (kg/h)	38.939*	37.437*	36.443	35.541	37.439	36.967
Integrated PI	0.909	0.918	0.925	0.937	0.904	0.915

* Statistically not significantly different from the baseline case at the 5% level.

values of NO_x emission are not statistically significantly different from the result for the baseline case whatever the policy goal is set for the FT control. The measures used in FT control seem, therefore, not so effective for reducing NO_x emission, and more advanced policies have to be formulated if NO or NO_2 has to be regulated for the intersection particularly.

What's more, all the policy goals evaluated by the VISSIM traffic model are also analyzed using SUMO with 30 simulation runs. The essential performance measures are compared for the optimization objectives in travel delay, fuel economy and integrated performance index in Table 8 and 9 respectively. While the two traffic simulators adopt different models in describing vehicle interactions and traffic dynamics, the absolute results of the performance measures in signal optimization are similar to each other. Taking the FT case as an example, the differences of the performance measures are mostly under 5% and many are even not significant. In addition, when the performance measures for different policy goals are compared with the base line case, or to each other, similar relation pattern can be observed for SUMO and VISSIM. The analyses we have done so far with VISSIM are therefore validated by the results from another microscopic traffic simulator.

Table 9 illustrates the experiment results for the VA signal control using SUMO and VISSIM. The conclusions that can be drawn from the results of the two simulators are largely identical. In dependent of what policy goal is set for optimization, the result of VA signal control outperforms the FT control in both traffic mobility and sustainability. Especially, more benefit is found regarding the improvement in traffic mobility. For example, more than 12% average travel delay could be reduced if the objective to minimize average delay per vehicle is applied for the VA control. On the other hand, the gain in fuel efficiency is around 2.6% when average fuel consumption is minimized. The results of applying the integrated index as the policy goal lead to the improved travel delay per vehicle as well as significant reduction in fuel and emissions, both total and individual gases.

Table 9
Optimization results for the VA signal control using both VISSIM and SUMO.

Performance measures	Optimal objectives					
	Avg. delay		Avg. fuel		Integrated PI	
	VISSIM	SUMO	VISSIM	SUMO	VISSIM	SUMO
Avg. delay (sec/veh)	17.237	18.091	22.422	22.812	19.377	20.017
Avg. fuel (g/km)	74.839	73.912	70.844	70.180	72.548	71.246
Total CO (kg/h)	37.965	36.777	32.430	31.415	33.830	32.858
Total HC (kg/h)	1.315	1.274	1.138	1.103	1.207	1.169
Total NO_x (kg/h)	2.104	2.039	1.949	1.888	1.924	1.901
Total emissions (kg/h)	41.385	40.091	35.466	34.678	36.697	36.004
Integrated PI	0.889	0.892	0.915	0.918	0.880	0.882

Conclusions

The current need to enhance traffic management and planning for mobility, energy efficiency and environment requires clear and comprehensive guidance and experience in real application. This is particularly important for cities with increasing traffic demand while traffic-induced emission pollution and fuel efficiency are still not considered or implemented in traffic planning practice. Simulation models are important tools for evaluating policy implementation by traffic measures in practice. This study presents a detailed modeling framework that integrates microscopic traffic simulator with instantaneous emission estimator to quantify fuel usage and emissions produced in traffic. A signal optimization engine based on genetic algorithm is added in the framework to implement different policy goals in mobility and sustainability.

The methodology is applied to evaluate different signal control policies through a case study at an intersection in a Chinese city. Two traffic simulation models, VISSIM and SUMO, are integrated in the framework, and they are calibrated based on traffic measurement before signal optimization. The emission estimator was also finely tuned using real vehicular emission measurement by a portable system. While a standard GA algorithm is coded for signal optimization, the performance of the GA operators in selection, crossover and mutation is compared and the most efficient combination is applied in the final application in policy analysis.

Two signal control schemes, fixed time and vehicle actuated, are optimized for different policy goals in the case study. The performance measures in mobility and sustainability are analyzed and compared for the optimal signal plans obtained. The final conclusions being reached can be summarized as follows:

- Almost all optimal signal plans contribute to significant improvement, in traffic mobility and sustainability, from the baseline case mimicked by a FT control.
- In terms of recognizing poor traffic conditions, total number of stops and total fuel consumption within a time interval do not seem to be effective objectives whereas average number of stops and fuel consumption per kilometer seem to be more reliable policy goals.
- The performance measures optimized for vehicle stop number and fuel consumption show a similar pattern, indicating average fuel consumption and stop number are exchangeable policy measures for this signal planning case.
- Apparent trade-offs between traffic mobility and environmental impacts are found in the analysis. An integrated performance index (including average delay, fuel consumption, and emissions) shows its advantage to balance conflicting policy goals in mobility and sustainability. In terms of environmental impacts, optimal signal plan leads to remarkable mitigation in total emissions, more significant than the improvement in fuel efficiency.
- The two microscopic simulation models, VISSIM and SUMO, are applied to assess the performance measures under different policy goals. The results are close to each other, therefore enhanced the validity of our conclusions.

- When comparing the performance measures of the two control schemes, the VA control outperforms the FT control when different policy goals are optimized. In particular, the improvement in traffic mobility is apparent whereas the mitigation of fuel and emissions is less evident.

Through the case study, the current microscopic modelling framework has shown its ability to optimize signal plans for a wide spectrum of policy goals. The result shows that the method is promising for implementation of the control objectives for energy and environment, although lengthy computation is still required during signal optimization. While a comprehensive analysis on performance measures under different policy goals was carried out, the case study is limited by the results from only a single intersection. Given the increasing interests in area-wide signal control in planning practice, our research focus has been recently extended to more advanced signal controls on larger network e.g. considering group-based control and coordination between intersections (Jin and Ma, 2014). In the mean time, the computational performance for such simulation-based optimization should be enhanced in our future work.

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