

# Multi-criteria evaluation of optimal signal strategies using traffic simulation and evolutionary algorithms

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**Abstract:** As a result of the continuous increase of motor vehicles in city areas, sustainability of road traffic in terms of energy and emission has become, in addition to mobility, one important aspect in the planning and management of transportation. This paper introduces a computational framework to model traffic impacts and optimize traffic control measures by integrating microscopic traffic simulator with instantaneous emission model and multi-objective evolutionary algorithm. The approach is applied for evaluation and improvement of traffic management measures mainly traffic signal plans, concerning not only travel delay but also energy and environmental consequences. A case study is presented to show the Pareto frontiers estimated using different strategies, or combination of optimization objectives.

**Keywords:** Multi-objective optimization; traffic signal control; mobility; energy efficiency; environment.

## 1 INTRODUCTION

The rapid increase of transport requirements, especially road transport, has brought challenges to sustainable development of our society with respect to energy consumption and traffic-induced pollutant emissions. At present, the transportation sector accounts for more than 20% of global energy consumption and road transport produces about 25% of principal greenhouse gases (GHG), considered to be the major factor of global climate change. Meanwhile, road traffic emissions are the main source of local air pollutants in urban areas including carbon monoxide (CO), nitrogen oxides (NO<sub>x</sub>), particulate matters (PMs) and so on. All of these emissions result not only in environmental problems but also add to the deterioration of human health and social economics. Therefore, management of traffic impacts has become one of the most essential and urgent aspects for sustainable transportation planning and management.

The conventional traffic management measures usually have an objective of improving the mobility performance reduction due to congestion e.g. minimizing total network delay in traffic signal control [Miller, 1963]. Traffic safety is, at the same time, often added as another concern when evaluating or developing management strategies. As mentioned, the negative impacts of road traffic in terms of fuel consumption, green house gases emissions and air pollutants have recently become additional important factors being considered in most planning and operation projects. Especially, it has been considered for optimizing various existing traffic measures and designing new Intelligent Transportation Systems (ITS). In order to implement sustainable traffic management in reality, it is essential to quantify energy and environmental impacts using traffic and emission models.

## 1.1 Traffic models

Road traffic is a highly complicated system composed of infrastructure components, vehicles and humans, and is involved with their interactions. Simulation models have become an indispensable tool for transport planning and management [Yang, 1997], aiming at improving transport mobility, enhancing driving safety and alleviating environmental impacts. Traffic models are classified into three levels: macroscopic, mesoscopic, and microscopic, each of which has its special properties concerning model details, complexity, computational characteristics etc.

Macro-models tend to represent road traffic as continuous flows without considering its internal elements. The formulation is inspired by e.g. differential equations based on fluid dynamics. Micro-models describe traffic as a multi-agent system with detailed representation of objects such as vehicles, pedestrians, signals, ITS systems etc. and their interactions [Yang, 1997]. Meso-models sit in between these two extremes, and often represent a traffic network simply as nodes and links. Besides route choices, individual vehicles are integrated as physical streams without considering their interactions. All the three levels have their own advantages and disadvantages. Micro-models can simulate road network in a high fidelity. They have the ability to replicate detailed aspects of individual behavior e.g. vehicles and drivers as well as to incorporate complicated traffic controls and ITS functions. Nevertheless, more information on traffic networks has to be collected, and thorough calibration of various agent models according to real data such as driver behavior is also important before application.

## 1.2 Modeling of emission impacts

One of the most fundamental problems for environmental impact analysis of road transport is how to model the levels of vehicle exhaust and non-exhaust emissions (CO<sub>x</sub>, NO<sub>x</sub>, HC, PM etc.) and fuel consumption accurately. The existing vehicle emission/energy models are often classified into aggregate and microscopic models e.g. [Ma et al., 2012]. Aggregate models usually apply static approaches to estimate total or average emission and fuel consumption. They are widely used for planning and evaluation of traffic environment. The models often require input data such as vehicle fleet composition, average traffic speed on road links, vehicle travel distance etc. For example, MOVES[Frey et al., 2003] and ARTEMIS[Keller and Kljun, 2007], developed by EPA and the EU commission respectively, are well-known aggregated emission models being applied in many transportation planning and management projects.

Recent research has raised concerns about detailed management of dynamic emission and energy consumption in local area. Microscopic emission models, calculating instantaneous emissions using inputs of vehicle running states, become one of the current research highlights thanks to their high resolution in evaluating dynamic emission impacts of vehicle fleet in operational transportation projects. An important aspect of the approach is that micro-scale models can be used in evaluation and improvement of traffic controls and operations. A number of microscopic emission models are popular in literature such as CMEM [Barth et al., 2000] and VT-Micro model [Rakha et al., 2004].

## 1.3 Sustainable traffic management

To achieve sustainable road traffic, the focus should be on not only mobility, but also energy and environment. One way of dealing with problem of this kind is to optimize traffic control, especially signal control in the urban context. Traffic signal timing is the technique which traffic engineers use to determine who has the right of way at an intersection

and is one of the most critical components, since it can control traffic flow patterns in congested urban areas. The current practice on urban traffic signal control systems mostly implement signal plans that optimizes mobility measures, such as vehicular delay or number of stops. It is however not fully clear whether and how minimizing vehicular delay and stop number may impact energy and environment. This indicates that the optimal signal timing strategies that maximize traffic mobility may not achieve least fuel consumption and emission or vice versa. One essential concern for this study is to formulate method able of finding the trade-offs between different goals. This will provide important information and tools for traffic planners in their decision makings.

## 2 METHODOLOGY

The boosting of computer power has promoted integration of traffic simulation and emission models for detailed traffic impact analysis [Boulter and McCrae, 2007]. The applications range from in-vehicle systems, dynamic traffic management to traffic calming and so on. In the state of the art of signal controls, emissions and fuel consumptions are, moreover, considered in development of optimal strategies. To fulfill control objectives incorporating energy and emission impacts, computational frameworks based on stochastic optimization algorithms, such as [Stevanovic et al., 2009], have been proposed.

### 2.1 Computational framework

When developing optimal traffic signal controls, it is common to have an objective function such as

$$\min_{\theta} O(\mathbf{x}, \theta), \quad \theta \in [\theta_{min}, \theta_{max}] \quad (1)$$

where  $\theta$  represents a vector of decisional variables with constraints in signal plan e.g. green time for each phase while  $\mathbf{x}$  describes other input variables to traffic system e.g. traffic demand. Conventionally, signal control objective is often formulated to represent mobility or efficiency of traffic system e.g. total travel delay. When other factors including environmental impacts are considered in active traffic management, various objective functions are considering surrogate measures like vehicle stops, energy consumption, pollutant emissions etc.

In order to implement the objective of eq.(1) in traffic management, a model-based computing framework is formulated in the figure 1. The basic idea is to quantify traffic by microscopic model given the inputs of travel demand, infrastructure supply and traffic control measures. Emission model gives a detailed estimation of vehicular emissions and fuel consumption by taking inputs of on-line vehicle running states from traffic models. Together, the two models contribute to the performance of the objective function. Since both microscopic traffic and emission models are often simulation models (e.g. third-party software), stochastic optimization approach [Spall, 2003] becomes an essential component in the framework to help find optimal control solutions. The application of the proposed framework requires well calibrated models to represent real traffic conditions as well as to estimate vehicular fuel consumption and emissions. The calibration of microscopic traffic model is by itself a highly complicated procedure. Aggregate traffic data is often used for the calibration purpose. Micro-scale emission models are normally developed from instantaneous vehicular emission data. They all have direct impacts on the result of optimal signal control being found.

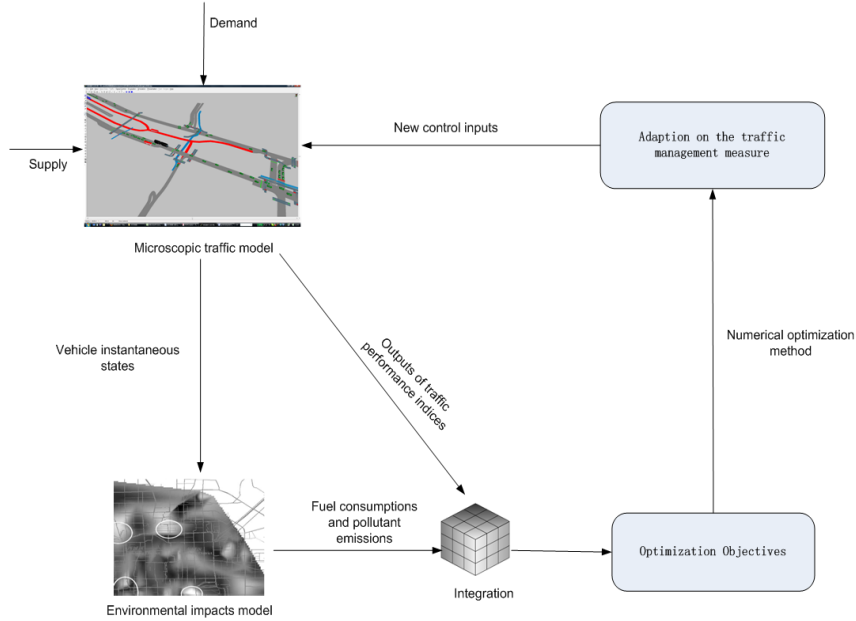


Figure 1: A computing framework to optimize traffic signal control.

## 2.2 Multi-objective evolutionary algorithms

Stochastic algorithms have become attractive approaches since they cope with systems that are random, highly nonlinear and easily disrupted by noise. Genetic algorithm (GA) is a evolutionary optimization technique inspired by Darwins theory about the survival of the fittest species. The approach normally starts with a random set of solutions (chromosomes) called a population. Solutions within the population crossover to form new chromosomes (offspring). The chromosomes selected in a population to be crossed (parents) are determined by their fitness measure. The higher the individual fitness is, the higher the chance to be selected to reproduce.

Multi-objective optimization (MOO), also known as multi-criteria optimization, is an optimization class that handles more than one objective e.g.

$$\min_{\theta} (O_1(\mathbf{x}, \theta), O_2(\mathbf{x}, \theta), \dots, O_n(\mathbf{x}, \theta)) \quad (2)$$

Traffic management is a natural application area that MOO methods may be applied. A conventional way to tackle the problems with more than one objective is to artificially convert the problem into a single-objective optimization. This has been popular in transport applications e.g. Li et al. [2004]. However, such approach requires artificial determination of weights to the different goals. Meanwhile, only a single solution that optimizes the objectives in a certain trade-off is found. This is however not the general case since MOO problems give rise to a set of trade-off solutions, known as Pareto-optimal solutions. Multi-objective evolutionary algorithms (MOEA) have been developed to particularly treat with multi-objective decision problems. This study adopts the non-dominated sorting genetic algorithm II (NSGA II), a fast and elitist multi-objective genetic algorithm capable of finding the Pareto-optimal solutions [Deb et al., 2002]. Figure 2 shows basic sorting schemes in the NSGA II heuristic. Solutions in the parent population  $P_t$  and offspring population  $Q_t$  are divided into different fronts, where the first front  $f_1$  is a non-dominated set in the current population. The second front is only dominated by the individuals of the

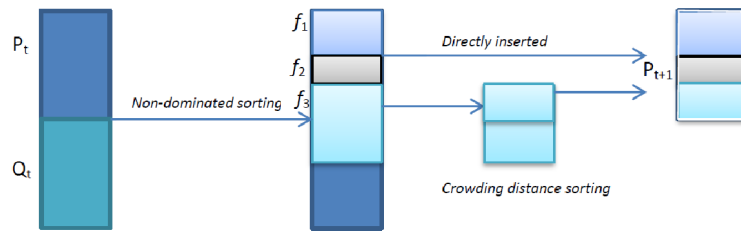


Figure 2: The NSGA II sorting scheme.

first front and the rest of the fronts follow this logic. All individuals situated in each front  $f_k$  are assigned rank values  $k$  based on which front they belong to. The ranking starts at one for the first front and increases by one for each subsequent front. When the hierarchy of the initial population is determined, the population is entered in a loop and renamed to  $P_t$ , where  $t$  is the current iteration number. If  $f_1$  exceeds the limitation of  $n$  solutions in the new population, a crowding distance comparison [Deb et al., 2002] will be performed to make the diversity of the solutions as high as possible. The other GA operators including selection for crossover and mutation used in the algorithm are somehow standard and are presented in previous study in single-objective signal optimization [Ma et al., 2011].

### 3 CASE STUDY ON SIGNAL CONTROL STRATEGIES

To demonstrate the simulation-based optimization framework, traffic signal control strategies at an isolated intersection, modeled in a previous study [Ma et al., 2011], is investigated in this case study. Traffic mobility and impact measures are used as objectives in the optimization process.

#### 3.1 Model implementation

The road network is built and simulated in VISSIM, a popular microscopic simulation software for transport decision makers. Figure 3 shows the configuration of network and its appearance in simulation. The intersection has four arms, each of which has five lanes, three straight through, one left-turn and one right-turn. The right-turn lane is not controlled by signal. It shares part of areas with motorcycle and bicycle lanes near the intersection. Traffic models of the simulated network has been calibrated using real measurement [Ma et al., 2011]. In the study, the average demand level being observed is applied in the simulation. Instantaneous states of each individual vehicle on roads are obtained from VISSIM and then used as inputs to emission models. Traffic performance indices can be directly obtained by running VISSIM.

Several micro-scale emission models are available after calibration using portable emission measurement system (PEMS) data [Ma et al., 2012]. Among them, the model taking the form of VT-Micro is computationally most efficient and thus used in this study to estimate fuel consumption, HC, CO pollutants etc.. After both VISSIM and emission estimation, information about the network mobility and impacts are obtained. An evaluation of the objectives selected for various goals can be further processed. To increase computational efficiency and conduct multiple runs of traffic simulation with different random seeds, the COM (Component Object Model) interface to the running objects of VISSIM is called in a program written in Python. The optimization mechanism is implemented in MATLAB, a high level numerical computing environment. NSGA II is implemented as a stochastic optimization engine able of calling the simulation objects in Python.

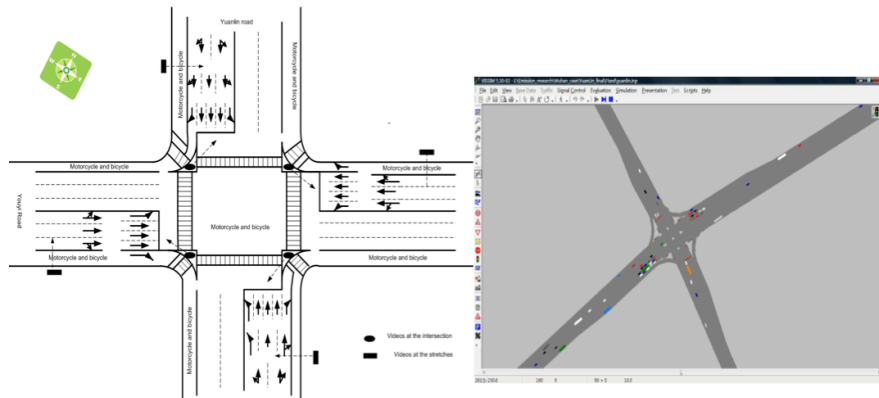


Figure 3: The configuration of the isolated signalized intersection.

The signal control used at the intersection is approximated by a fix-time controller with time plan showing in Table 1. The current setting is optimized for delay using TRANSYT. The green times of each phase are chosen as control parameters for the optimization, resulting in four control parameters. The cycle length is bounded to a reasonable range.

### 3.2 Evaluation results

The optimization objectives in this study include the average delay for all vehicles in the network, the average stops per vehicle and the average fuel consumption. Investigation considering trade-offs between these objectives is done, where the optimization objectives are set against each other in the following way:

- Average delay versus average stops per vehicle;
- Average delay versus average fuel consumption per vehicle.

The proposed stochastic optimization algorithm, NSGA II, is applied to find the optimal trade-off solutions. The process is obviously more computationally expensive than single-objective optimization because of the increase of objective dimension. Due to the limitation of computing power, a population size of 20 is used for each GA generation. The heuristic employs a 20 generation evolution. For each gene group of control parameters, 5 simulation runs with different random seeds are adopted. Each run includes one-hour traffic simulation. Figure 4 shows the Pareto-optimal solutions achieved in the first two cases. The left graph shows the best frontier achieved by the algorithm when delay and vehicle stops are minimized. The point with the minimal delay is allocated furthest to the upper-left whereas the point with the minimal stops is allocated down-right. Between those extremes, solutions with different trade-offs between those objectives exist. Table 2 compares the two extreme solutions with the baseline case. The control strategy minimizing travel delay leads to statistically significantly worse environmental impacts, though the mobility is the most efficient. The right graph of the figure 4 shows the best frontier achieved by the algorithm when fuel consumption and travel delay are minimized together. Again, table 3 compares the two extreme solutions with the baseline case. The control strategy to minimize fuel consumption achieves the best performance concerning environmental impacts.

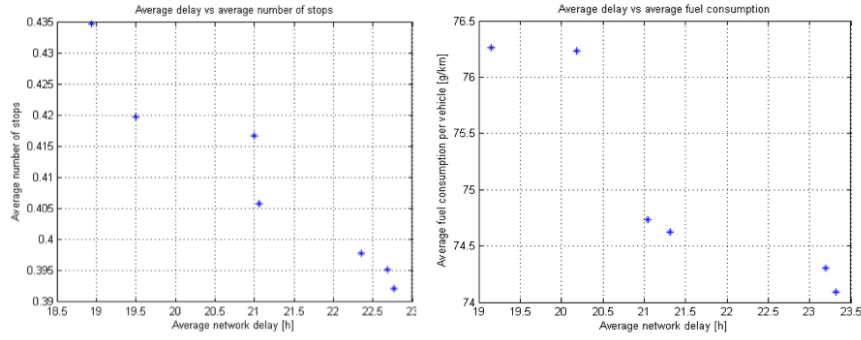


Figure 4: The final Pareto-optimal frontier estimated for two multi-objective strategies.

Phase order	Description	Cycle length	Green time
1	Left-turn traffic on east-west	145	18
2	Direct traffic on east-west	145	78
3	Direct and left-turn traffic from north	145	15
4	Direct and left-turn traffic from south	145	15

Table 1: Approximated signal timing at the isolated intersection (time in second).

#### 4 SUMMARY AND FUTHER STUDY

This paper demonstrates that multi-criteria analysis of optimal traffic control strategies may help decision makers to choose the most appropriate policy or control parameters when different aspects of traffic system needs to be managed. The study proposes an integrated modeling framework and software implementation that combines microscopic traffic and emission models with advanced evolutionary algorithms. The case study in signal optimization at an isolated intersection shows clear result that different control strategies may lead to different consequences. However, the computational cost of the proposed framework is still quite expensive. To target detailed application in reality, more efficient software implementation is still necessary. The signal control in the study did not consider many uncertainty factors in traffic system such as fluctuating demand levels and traffic composition. They should be included in the future studies.

Strategies	Signal plan	Traffic measures			Emission and fuel consumption				
		delay [h]	stops	speed [km/h]	HC [g/km]	CO [g/km]	Fuel [g/km]	CO <sub>2</sub> [g/km]	
Baseline	[18, 78, 15, 145]	avg.	24.61	0.434	34.13	0.38	10.11	76.05	265.56
		std.	0.59	0.007	0.19	0.014	0.12	0.88	3.94
min $O_{stop}$	[10, 89, 12, 142]	avg.	22.75	0.397	34.74	0.352	9.66	74.32	257.60
		std.	0.42	0.003	0.22	0.008	0.255	0.8	3.96
min $O_{delay}$	[10, 53, 10, 11, 103]	avg.	18.94	0.435	36.07	0.389	10.41	76.03	267.12
		std.	0.63	0.012	0.25	0.01	0.28	0.94	4.16

Table 2: comparison of traffic performance and environmental impacts when coping with  $\min\{O_{delay}, O_{stop}\}$ .

Strategies	Signal plan		Traffic measures			Emission and fuel consumption			
			delay [h]	stops	speed [km/h]	HC [g/km]	CO [g/km]	Fuel [g/km]	CO <sub>2</sub> [g/km]
Baseline	[18, 78, 15, 15, 145]	avg.	24.61	0.434	34.13	0.38	10.11	76.05	265.56
		std.	0.59	0.007	0.19	0.014	0.12	0.88	3.94
min $O_{delay}$	[11, 52, 10, 11, 103]	avg.	19.15	.439	36.00	0.393	10.51	76.26	268.18
		std.	0.68	0.013	0.26	0.011	0.327	0.956	4.212
min $O_{fuel}$	[12, 90, 10, 11, 145]	avg.	23.32	.0397	34.56	0.345	9.566	74.09	256.24
		std.	1.09	0.006	0.42	0.01	0.12	0.72	3.87

Table 3: comparison of traffic performance and environmental impacts when coping with  $\min\{O_{delay}, O_{fuel}\}$ .

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