Bi-level Hybrid Algorithm for Greener Environment via Vehicular Networks in a Single Intersection

Kun Liu[1,2], Jianqing Li[2], Wenting Li[2], N. X. Xiong[3]

[1] School of Information Technology, Beijing Normal University at Zhuhai, China
[2] Faculty of Information Technology, Macau University of Science and Technology, Macau
[3] School of Optical-Electrical and Computer Engineering, University of Shanghai for Science and Technology, China
1309853gii30001@student.must.edu.mo, jqli@must.edu.mo, eva-lwt@163.com, xiongnx@qq.com

Abstract

In this paper, we propose a bi-level optimization model (BLOM) with improved hybrid metaheuristics. The hybrid GA and PSO algorithm is applied in both upper-level and lower-level model. This improved hybrid algorithm differs from the general hybrid algorithm which GA or PSO is applied in the single upper-level or lower-level model. BLOM is intended to schedule the phases of each isolated traffic signal and eco-driving environmentally. The upper-level optimization model (ULOM) considers the real-time traffic characteristics of the traffic flows near the signalized road intersection. At the same time, vehicles in the lower-level optimization model (LLOM) retrieve the real-time traffic signals using vehicular networks. Then, the traffic signals update the schedule and the vehicles are optimized motion states for greener environment factor respectively. We evaluate the performance of BLOM in a single road intersection using OMNET++ and SUMO. From the simulation results, we conclude that the BLOM with improved hybrid algorithm reduce fuel consumption and CO_2 emissions compared with Maximize Throughput Model (MaxTM). Moreover, compared with the ordinary single algorithm, the proposed improved hybrid algorithm decreases the average operation cycle.

Keywords: Vehicular communication, Improved hybrid algorithm, Bi-level optimization, Greener environment

1 Introduction

Nowadays, the transport sector is a huge consumer of energy. It accounts for around 37% of global primary energy use and energy-related CO_2 emissions in 2013 [1]. Transportation is almost completely reliant (95%) upon petroleum products which are non-renewable resources [2]. Fossil oil will be exhausted in future [3]. Moreover, the burning of fossil fuels produces 87% of human carbon dioxide emissions [4]. Carbon dioxide (CO_2) is the primary greenhouse gas (GHG) often used to compute the global warming potential (GWP) [5]. So, for greener environment, one effective way applied to transportation for carbon dioxide emissions reduction is to reduce fossil fuel consumption [6-7].

Vehicular networks are responsible for the communication between moving vehicles in a certain street environment. A vehicle can communicate with another vehicle directly which is called Vehicle to Vehicle (V2V) Communication, or a vehicle can communicate with an infrastructure such as a Road Side Unit (RSU), known as Vehicle to Infrastructure (V2I) Communication [8-9]. Vehicle self-organizing ad hoc networks with V2V and V2I are called vehicle ad hoc networks (VANETs). Due to their unique characteristic such as high dynamic topology and predictable mobility, VANET is generally used to improve transport efficiency and safety [10-11].

Each vehicle equips motion state data collector called On Board Unit (OBU). Then, the transportation management system will optimize the traffic efficiency for greener environment because RSUs and vehicles share traffic data via vehicular networks. In [12], authors have presented the fuel-optimized operating strategies of vehicles under cruising process. The vehicles group into platoons at the same cruising speed based on V2V communications. For reducing the emissions scheme, a decentralized signal control technique is proposed in [13] for reduction of vehicle stops using vehicle arriving information collected by inter-vehicle communication.

The urban transportation network design problem is usually formulated as a bi-level problem or a leader-follower problem. The upper level problem is the leader's problem, or the problem of the decision maker, who plans or manages the transport network. The lower level problem is the followers' problem [14]. The bi-level structure allows the decision maker to consider the reaction of the followers and improve the network to influence the choice of followers but has no direct control on their choice. This structure does not

*Corresponding Author: Kun Liu; E-mail: 1309853gii30001@student.must.edu.mo
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allow the travelers to predict the decision of the leader, but only allows them to determine their choice after knowing the decision of the leader [14]. In the transportation management system, RSUs can be called decision maker in this bi-level problem for greener environment. The RSUs plan traffic signal scheme using vehicle motion information collected by inter-vehicle communication. The vehicles equipped with OBU can be named the followers to move with the optimal process of eco-driving based on received traffic signal plans sent from the RSU using vehicular networks.

In this paper, we propose a bi-level optimization model (BLOM) in a single road intersection that considers the transportation management system is a bi-level programming model. The introduced model is intended to schedule traffic signals at each road intersection, which calculating and predicting energy efficiency to reduce the expected total fuel consumption and CO_2 emissions at each road intersection. Meanwhile, drivers adjust the vehicle moving state due to the traffic signal schedule known in advance. Then, each vehicle will be reduced fuel consumption. The improved hybrid algorithm is employed to improve calculation efficiency in upper-level and lower-lever model, respectively.

The remainder of this paper is organized as follows: In Section II, we discuss the previously propose in this field. Then, we present the consideration and details of BLOM in Section III. The BLOM is applied in a case and the model performance is evaluated in Section IV. Finally, Section V concludes this paper.

2 Related Work

Several researches have attempted to look for methods of fuel economy and CO_2 emission [5-6]. A study in [6] indicated that idling, driving at very high speed and aggressive driving influence vehicle fuel economy. Accelerating and decelerating have higher fuel consumption. So smoother driving style with less accelerating and decelerating called eco-driving was tested to reduce fuel consumption by an average of 27% for heavy vehicle drivers [7]. Studies in [8] showed that the overall traffic flow will be smoother if vehicles use the dynamic eco-driving technique. In [9-12] a traffic signal control algorithm in Vehicular Ad Hoc Network (VANET) was proposed to smooth traffic flow with intelligent transport systems (ITS) technology. ITS is an integration of software, hardware, traffic engineering concepts and communication technology for safer, more efficient and more environment friendly transportation [13]. However, shorter delay and waiting queue length achieved with these traffic signal control algorithm are not same to reduce fuel consumption and CO_2 emission. For example, higher mean velocity tends to lower delays and larger throughput with many traditional traffic signal optimal algorithms [9, 14-15], but too high speed is unfavorable for fuel-economy and CO_2 emission. [16] implied that driving in the optimal cruise speed without acceleration and deceleration as possible would get the smallest fuel consumption and CO_2 emission per mile.

In recent years, researches based on intelligent transport systems (ITS) are promoted to build a more environmentally-friendly motorized society [17-18]. ITS's fuel efficiency and CO_2 reduction approaches are included in traffic reduction and fuel consumption and CO_2 emission reduction [19]. The latter can be implemented by some approaches: driver behavior promotion, ITS technology and so on. The main focus of this article is to propose and discuss an integrated model for minimizing fuel consumption and CO_2 emissions with ITS technology.

A connected vehicle technology sharing vehicle speed information is used for better fuel economy of a fleet including six vehicles. Speed synchronization of the vehicles in the fleet is implemented with Vehicle-to-Vehicle and/or Vehicle-to-Infrastructure communication [20]. In [21], a new "economical" geocast (EG) protocol with VANETs was created to save fuel. The drivers can choose a new route based on minimizing trip fuel consumption if an accident happened on the highway ahead, but that research was not included in a classical traffic scenario, e.g., a single intersection with traffic signal control that is a primary unit to build the whole urban transportation network. The impact of velocity, acceleration and deceleration on fuel consumption also wasn't discussed.

In [22], the microscopic analysis indicated that instantaneous vehicle speed has the greatest impact on the distanced-based emission and fuel consumption factors, followed by the time-based emission and fuel consumption rates based on a series of on-road test conducted in Hong Kong. A limitation of this study was the use of a single test vehicle for each category, but the results highlighted general emission behavior under actual on-road driving conditions in urban areas.

A three-tier structure is proposed to realize branch-and-bound-based dynamic traffic light control for smoothing vehicles' travel, and therefore the vehicles' CO_2 emissions can be reduced [23]. In this safety-based branch-and-bound (SBB) algorithm, the traffic lights are controlled to let vehicles pass the intersections with less waiting time, but less travel time is not equal to less fuel consumption because the fit stable speed is better for fuel economy and CO_2 emissions [24-25]. It is not also reasonable for the current speed as the recommended speed if the remaining green light time is long enough for the vehicle to go through the intersections since the current speed doesn't mean it's the fittest speed for reducing fuel consumption [25].

Two green driving suggestion models, Maximize Throughput Model (MaxTM) and Minimize

Acceleration and Deceleration Model (MinADM), are proposed to improve SBB algorithm above for minimizing the CO_2 emissions. Simulation results indicate that MaxTM and MinADM perform much better than SBB algorithm [26]. However, the optimization for reducing vehicles' CO_2 emissions is achieved only in OBU (on-board unit) side but not in RSU (road side unit) side. Traffic signal control in RSU can be at work in optimization of fuel economy [24]. In [26], the study of the OBU driving action, i.e., acceleration and deceleration on brake is imprecise but that driving actions have a demonstrable influence on fuel consumption and CO_2 emissions.

In traffic signal control solutions, Yan et al. proposed a Branch and Bound (BB) approach to control traffic lights in a simple intersection with the objective of minimizing the evacuation time of the intersection [24]. Li et al. improved the BB algorithm and present an open traffic light control model (OTLCM) for reducing vehicles' CO_2 emissions in a single intersection. This model implicated less waiting queues is equal with minimizing fuel consumption and CO_2 emissions [25].

Apart from traffic signal control in RSU side, driving states control in the OBU side smooth the vehicle speed to minimize fuel consumption and CO_2 emissions. Hornung et al. compared the fuel consumption before and after eco-driving among a group of seventy-nine participants. The test results indicated that driving more smoothly led to cut 17% fuel consumption [26]. Lee et al. presented a green driving suggestion model, Maximize Throughput Model (MaxTM) [24]. MaxTM calculated a recommended speed in the OBU side for maximizing the possibilities of passing through the intersection by a smooth eco-driving style.

Unlike the optimization only in one side, the bi-level optimization model will reduce expected costs in both sides. In [23], a bi-level road network optimization model was presented. The upper-level model aimed to minimize the yearly cumulative costs consisting of construction cost, maintenance cost, energy consumption cost, total travel time cost, cost relevant to pollutants and cost relevant to greenhouse gases. The lower-level model was a user equilibrium traffic assignment model including traffic flow, average travel speed and travel time on each link. This model focused on the optimization of the set of given road candidates in a long term evaluation period with the macroscopic view. In this study, three heuristics such as Genetic Algorithm (GA), Simulated Annealing (SA) and Artificial Bee Colony (ABC) are employed respectively. Ferguson et al. then designed the upper-level optimization model that only concentrated on environmental costs calculated with the macroscopic parameters such as average speed, link capacity, average travel time and so on with GA [27]. Chen et al. also adopted macroscopic model to estimate emissions with GA [28].

Different from the existing studies on this issue, in this paper, the bi-level optimization model is proposed to minimize fuel consumption and CO_2 emissions by considering traffic information nearby the intersection including the traffic signal control in the RSU side and Instantaneous vehicle motion states in OBU sides. This model adopts three solution methods: GA/GA (the upper-level model and lower-level model both adopt GA), PSO/PSO (the upper-level model and lower-level model both adopt Particle Swarm Optimization algorithm), and GA-PSO/ GA-PSO (the upper-level model adopts hybrid GA and PSO while the lower-level model adopts hybrid GA and PSO too). In the traffic signal controller, RSU in the upper-level model collects the vehicle motion data nearby the intersection. Then, RSU calculates the total fuel consumption of all the vehicles nearby the intersection in different traffic signal phasing schemes. The optimal traffic signal phasing scheme will be chosen with 3 heuristic algorithms. Meanwhile, OBUs in the lower-level model receive the present traffic signal phasing scheme sent by RSU with one algorithm to calculate fuel consumption with different vehicle instantaneous speed and acceleration. The optimal vehicle motion state will be chosen for the vehicle to move with the same 3 heuristic algorithms. Moreover, the 3 heuristic algorithms are compared in several experiments, which is detailed discussed in Section 3.

The rest of this paper is organized as follows. The proposed system models are discussed in Section 3 and evaluated in Section 4. Finally, Section 5 concludes this paper and proposed the future work.

3 System Model

In this section, a bi-level optimization model is proposed for minimizing fuel consumption and CO_2 emissions in one intersection. In this model, for communication to occur between vehicles and the RSU, vehicles must be equipped with some sort of radio device or OBU that enable short-range wireless ad hoc networks to be formed [10]. OBUs must also obtain vehicle instantaneous motion state data such as velocity, acceleration and deceleration from the vehicle management system. Vehicles must also be fitted with detailed position information receiver such as Global Positioning System (GPS) or Differential Global Positioning System (DGPS) ones, which transmit the coordinate of the vehicle's location to the OBU. Then, vehicles optimize speed and acceleration with minimizing fuel consumption according to the present traffic signal phasing scheme sent by the RSU. The fixed RSU must be in place to collect vehicle motion state and location data sent from OBUs, then calculate the optimal traffic signal phasing scheme according to the total fuel consumption of all the vehicles nearby the intersection. The RSU communicates with an OBU on one vehicle via vehicle-to-infrastructure protocol (V2I) directly if the direction between them is close enough, or through other vehicles as transfer stations [10, 16-17]. The wireless communication between two vehicles directly is called vehicle-to-vehicle communication (V2V), as shown in Figure 1. The communicating vehicles compose vehicular ad hoc networks (VANETs).

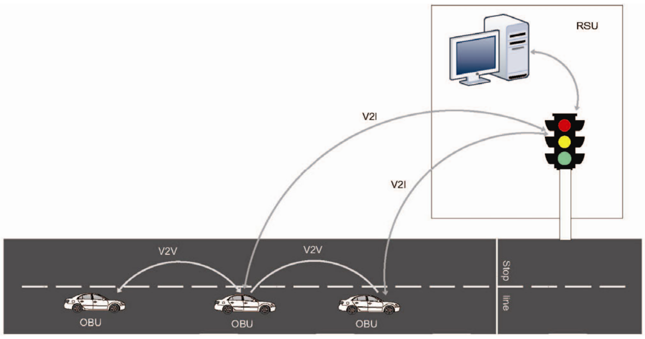


Figure 1. V2I and V2V communication

3.1 Bi-level Optimization Model

3.1.1 Introduction of the Bi-level Programming (BP) Model

In this paper, the target of the traffic signal control is to minimize the full consumption and CO_2 emissions. So, the objective function of the upper-level programming model is minimizing the full fuel consumption and CO_2 emissions in the single intersection, denoted by E_{up} shown in Eq. (3).

E_{up} is summed by the fuel consumption produced by all vehicles near the crossing in different motion states such as cruising, acceleration, brake and stop. The fuel consumption in each motion state is relative with the traffic signal scheme G and the vehicle motion data such as v , a_1 , a_2 . It is calculated by the fuel consumption and CO_2 emission model detailed in the following Section 0. The vector G is the decision vector of the upper-level decision-makers, represented as the scheme of the traffic signal phasing.

$$(U)\ \min_{G} E_{up}(G, v, a_1, a_2) = \sum_{t=0}^{T}\sum_{i=1}^{N}(e_{1i}^t + e_{2i}^t + e_{3i}^t + e_{4i}^t + e_{5i}^t) \tag{3}$$

$$s.t.\ G_t \in \{0,1\}, t = 1, 2, ..., \frac{T}{d} \tag{4}$$

Where

T : total time

d : time slot unit of the traffic signal change

t : traffic signal phase in the total time

N : traffic in the total time

G : scheme of the traffic signal phasing

G_t : traffic signal at the phase t . 0 is denoted as the red traffic light, 1 as the green traffic light

v : vehicle's speed

a_1 : brake deceleration

a_2 : starting acceleration

e_{1i}^t : fuel consumption with the cruising speed from the entrance of the intersection in the phase t of the vehicle i

e_{2i}^t : fuel consumption with the reduced speed before stop at the crossing in the phase t of the vehicle i if the vehicle i can't pass the crossing in the phase t

e_{3i}^t : fuel consumption while stopping at the crossing at the red light in the phase t of the vehicle i if the vehicle i can't pass the crossing in the phase t

e_{4i}^t : fuel consumption while accelerating through the crossing after stopping before the stop line in the phase t of the vehicle i if the vehicle i can't pass the crossing

e_{5i}^t : fuel consumption with the cruising speed after passing through the crossing in the phase t of the vehicle i

$v = v(G)$, $a_1 = a_1(G)$ and $a_2 = a_2(G)$ are usually called the reaction or response functions. They are implicitly defined by Eq. (5). The objective function of the lower-level programming model is also minimizing the full fuel consumption and CO_2 emissions in the single intersection, denoted by E_{down} . v, a_1, a_2 are the decision vector of the lower-level decision-makers, represented as the vehicles' motion data. Constraint (6)-(8) are the range restriction of the decision variables. Constraint (9)-(13) are represent the calculated fuel consumption in different traffic lights and different motion sates.

3.1.2 Solution of the Bi-level Programming Level

The BP model is a non-linear programming (NP) problem [32]. It is proved that there must be an Pareto optimal solution of BP model no matter whether the objective function is convex programming [33-34], and the intelligent algorithms is the best strategy to solve this kind of problems.

Genetic Algorithm (GA) is an iterative intelligent search algorithm based on an analogy with the process of natural selection (Darwinism) and evolutionary genetics [35]. The search aims to optimize a user-defined function (the function to be optimized) called the fitness function. To perform this task, GA maintains a "population" of candidate points, called "individuals", over the entire search space. At each iteration, called a "generation", a new population is created. This new generation generally consists of individuals which fit better than the previous ones into the external environment as represented by the fitness function. As the population iterates through successive generations, the individuals will in general tend toward the optimum of the fitness function [35].

The PSO is another iterative intelligent search algorithm based on imitation of the movement of living organisms, i.e. flocks of birds or herds of animals. In contrast to the GA, the PSO does not use any evolutionary operations, and requires only primitive mathematical operators, making it easy to be coded. The PSO searches for a global optimum by adjusting the position of each potential solution, called a particle, toward two optimization directions simultaneously: the local optimization is the best location in the past movement history of each particle, while the global optimization is the best location in the past movement history of the swarm. These features achieve faster convergence than the GA [30]. However, the PSO has a problem of premature convergence, due to the lack of diversity [29, 31].

$$(L)\ \min_{v,a_1,a_2} E_{down}(G,v,a_1,a_2) = \sum_{t=0}^{T}\sum_{i=1}^{n}(e_{1i}^t + e_{2i}^t + e_{3i}^t + e_{4i}^t + e_{5i}^t) \tag{5)}$$

$$s.t.0 < v \le v_{\max} \tag{6}$$

$$s.t.a_{1\max} \le a_1 < 0 \tag{7}$$

$$s.t.0 < a_2 \le a_{2\max} \tag{8}$$

$$s.t.e_{1i}^t = \begin{cases} e_{1i(1)}^t, G_t = 0 \\ e_{1i(2)}^t, G_t = 1 \end{cases} \tag{9}$$

$$s.t.e_{2i}^t = \begin{cases} e_{2i(1)}^t, G_t = 0 \\ e_{2i(2)}^t, G_t = 1 \end{cases} \tag{10}$$

$$s.t.e_{3i}^t = \begin{cases} e_{3i(1)}^t, G_t = 0 \\ e_{3i(2)}^t, G_t = 1 \end{cases} \tag{11}$$

$$s.t.e_{4i}^t = \begin{cases} e_{4i(1)}^t, G_t = 0 \\ e_{4i(2)}^t, G_t = 1 \end{cases} \tag{12}$$

$$s.t.e_{5i}^t = \begin{cases} e_{5i(1)}^t, G_t = 0 \\ e_{5i(2)}^t, G_t = 1 \end{cases} \tag{13}$$

In this paper, hybrid GA-PSO/GA-PSO is selected to solve both upper-level and lower-level optimization problems. The lower-level model is restricted with the traffic signal phasing calculated by the upper-level model. The operating mechanism of the bi-level programming model is shown by the following flow diagram presented in Figure 2.

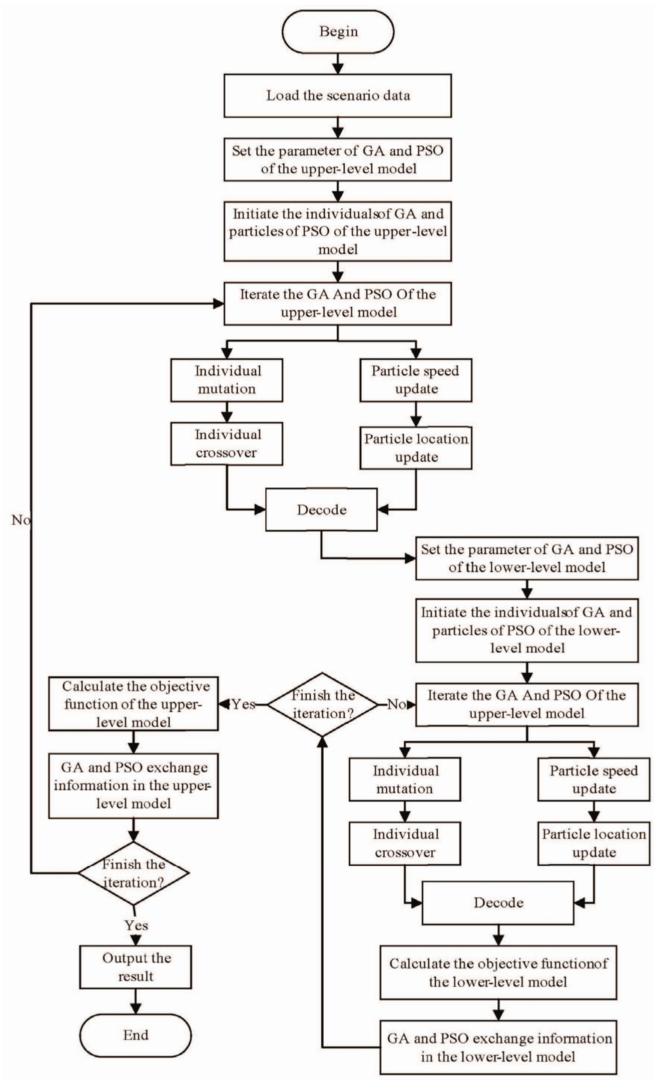


Figure 2. Improved hybrid algorithm workflows of the proposed model

The upper-level model initializes the intersection scenario and vehicle motion data which will be sent to the lower-level program model simultaneously. The parameters of the upper-level model for GA are set up such as population size, crossover rate, mutation rate and max generation, and the parameters of the upper-level model for PSO are set up such as population size, speed update rate and inertia factor.

Then, the population of GA and PSO in the upper-level model are initiated. The population of GA is the set of individuals which are coded traffic signal schemes. The total population size is set 4N which is divided into 2N separately for GA and PSO, as shown in Figure 3. The population of PSO is the set of particles which are coded traffic signal schemes. Then, GA and PSO is iterated respectively. GA performs genetic operations such as mutation and crossover. At the same time, PSO performs particle operations such as particle speed and location update. After evolution operation, GA and PSO decodes respectively that means traffic signal schemes recover from binary codes in the upper-level model to send to the lower-level model.

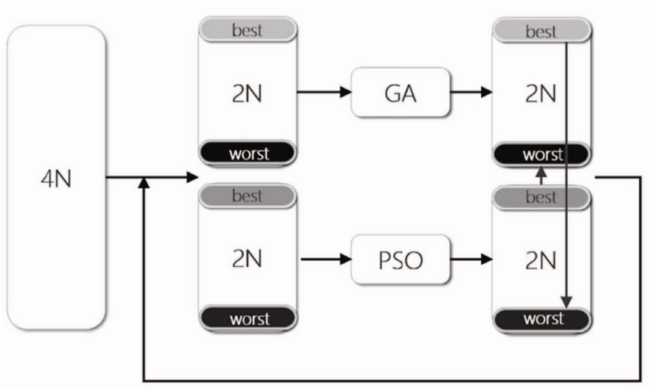


Figure 3. Hybrid GA-PSO/GA-PSO in upper-level and lower level optimization model

In the lower-level model, the population of the lower-level model is initiated. The individuals of GA and particles of PSO in the lower-level model are initiated. After initiation, The parameters of the lower-level programming model for GA are set up such as population size, crossover rate, mutation rate and max generation, and the parameters of the lower-level programming model for PSO are set up such as population size, speed update rate and inertia factor.

Then, the population of GA and PSO in the upper-level model are initiated. The population of GA is the set of individuals which are coded vehicle motion state such as speed and acceleration. The population of PSO is the set of particles which are coded traffic signal schemes. After that, GA and PSO is iterated respectively. GA performs genetic operations such as mutation and crossover. At the same time, PSO performs genetic operations such as particle speed and location update. After evolution operation, GA and PSO decodes respectively that means vehicle motion states recover from binary codes in the lower-level model.

Vehicle motion state data are sent to the transportation simulation model to select the optimal vehicle motion state value since the objective function of the lower-level model is the total fuel consumption is least when the traffic signal scheme is decided in the upper-level model. Then, GA and PSO exchanges information in the lower-level model that means the optimal value with PSO in the lower-level model replaces the worst value with GA in the lower-level model and the optimal value with GA in the lower-level model replaces the worst value with PSO in the lower-level model shown in Figure 3. The populations of GA and PSO in the lower-level model both update to continue iterating until iteration finished.

The lower-level model returns traffic signal schemes to the upper-level model. The optimal values of upper-level model with GA and PSO are calculated respectively for the least fuel consumption as the objective function. Then, GA and PSO exchanges information in the lower-level model that means the optimal value with PSO in the upper-level model replaces the worst value with GA in the upper-level model and the optimal value with GA in the upper-level model replaces the worst value with PSO in the upper-level model. The populations of GA and PSO in the upper-level model both update to continue iterating until iteration finished. Finally, the global value will be selected to output the final result.

3.2 Fuel Consumption and CO2 Emission Model

The bi-level optimization model uses the vehicle fuel consumption and CO_2 emission model (FCCEM) to calculate the objective function. The FCCEMs fall into the two categories: macroscopic and microscopic FCCEMs. The macroscopic FCCEMs generally compute fuel and emission rates based on average link speeds without regarding transient changes in a vehicle's speed and acceleration as it travels on a highway network. On the contrary, the microscopic FCCEMs predict vehicle fuel consumption and emissions using instantaneous speed and acceleration which is more suitable for the microscopic analysis of transportation management with ITS technology [34].

In this paper, the microscopic FCCEM, namely the Virginia Tech microscopic (VT-Micro) emission model, is adopted to calculate fuel consumption because it is a microscopic transportation environment that vehicles pass a single intersection. The VT-Micro model was developed as a regression model using chassis dynamometer testing data collected at the Oak Ridge National Laboratory (ORNL). These data include the vehicles' instantaneous speed and acceleration [35]. The statistical results indicated the VT-Micro model is a good fit for fuel consumption (R^2=0.995) [36].

Then, the CO_2 emission is calculated according to the perfect linearity correlation between the CO_2 emission rate and fuel consumption one [37].

4 Case Study

4.1 Case Introduction

The performance of the bi-level optimization model with the GA-PSO/GA-PSO hybrid algorithm is evaluated and simulated by OMNET++ and SUMO, which is realized vehicles passing a single intersection as the microscopic traffic flow with the cellular automata (CA) model.

In our previous work, the bi-level optimization model with GA/GA was proved that its performance is better than Maximize Throughput Model (MaxTM) [38]. In this section, the following six experiments focus on comparing the proposed hybrid scheme with other two non-hybrid algorithms, namely GA/GA and PSO/PSO proposed in our foregoing work.

4.2 Simulation Setup

The proposed scheme is evaluated in a single intersection with traffic signals, which is shown in Figure 4. Road 1 (R1) and Road 2 (R2) are two orthogonal 2-way and 2-lane roads. R1 is a major road in addition to R2 as a minor road. The default value of the distance from the starting point of each road to the stop line before the intersection is 300 meters. The default distance between two stop lines is 30 meters.

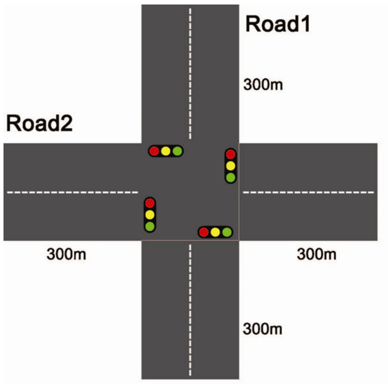


Figure 4. A single intersection with traffic signals

For simplicity, in our case study, we suppose that vehicles move only straight in R1 and R2 without changing lanes. It is also assumed that the traffic flow in the roads has the following rate relationship: R1:R2=2:1. It is assumed that it is same of the traffic flow in opposite directions of the same road.

Note that the vehicles' occurrence time and arrival rate are independent of each road.

For simplicity, the following assumptions are considered.

(1) The saturated traffic flow is set as 1000 vph.

(2) In our cast study, the total fuel consumption is mainly analyzed since that CO_2 emissions are calculated easily with the linear relation to the fuel consumption [37].

(3) The road traffic data are sent successfully without package dropping and transmission delay.

(4) The allowed maximum speed S_{max} is 80 km/h, S_{min} is 0 km/h, the maximum acceleration a_{max} is 4 m/s^2, and the maximum deceleration -a_{max} is -10m/s^2.

(5) The maximum transportation simulation time is 360s.

4.3 Simulation Study

(1) Experiment I: The optimal values of the fuel consumption with three algorithms are compared in different iteration times in the bi-level optimization models.

(a) The upper-level iteration times change from 30 to 60 at 10 intervals when the lower-level iteration times keep 20. The vehicle arrival rate is 200 vph and the saturation arrival rate is 1000vph. The upper-level population is 20, while the lower-level one is 10. The traffic signal change time slot unit is 8 seconds. The simulation result is shown in Figure 5. The figure indicates that the convergence of GA-PSO/GA-PSO is obviously better than other two algorithms while the upper-level iteration time is increasing. The diversity of GA-PSO/GA-PSO is much better than PSO/PSO which is premature when the iteration times are small. The convergence of GA/GA is better than PSO/PSO, but the optimal value of GA-PSO/GA-PSO is superior to GA/GA.

(b) The lower-level iteration times change from 10 to 40 at 10 intervals when the upper-level iteration times keep 50. The other setup parameters are same to Experiment I (a). Figure 6 shows the convergence of GA-PSO/GA-PSO is very obviously better than other two no-hybrid algorithms while the lower-level iteration time is increasing. The fuel consumption is on the decline as the iteration times increase. Figure 6 indicates that the PSO/PSO is premature and the convergence of GA-PSO/GA-PSO is much faster than GA/GA.

(2) Experiment II: The running time with the three algorithms are compared in the different iteration times.

(a) The upper-level iteration times change from 30 to 60 at 10 intervals when the lower-level iteration times keep 20. The other setup parameters are same to Experiment I (a).

Figure 7(a) indicates the running time of the three algorithms show an upward tendency when the upper-level iteration times are increasing. The running time of the GA-PSO/GA-PSO is the least in the three algorithms.

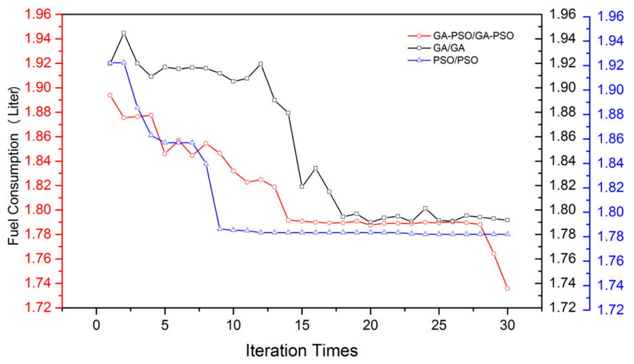
(b) The lower-level iteration times change from 10 to 40 at 10 intervals when the upper-level iteration times keep 50. The other setup parameters are same to Experiment I (b).

Figure 6(b) indicates the running time of the three algorithms show an upward tendency when the lower-level iteration times are increasing. The running time of the GA-PSO/GA-PSO is the least in the three algorithms.

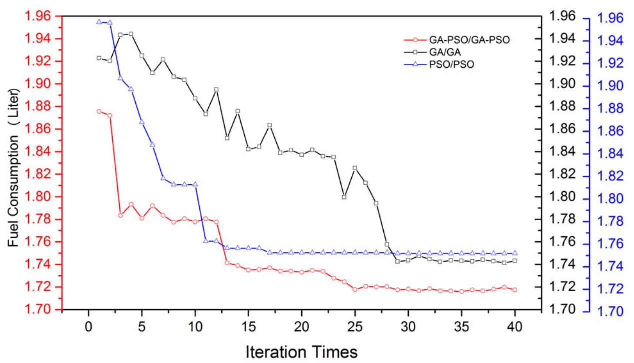
The result in this experiment shows the upper-level model with the GA and the lower-level model with the PSO are much fitter than the no-hybrid algorithm because the decision variable of the upper-level model, namely the traffic signal phasing scheme is discrete and the decision variable of the lower-level model, namely the vehicle motion state is successive. Thus, the GA-PSO/GA-PSO hybrid algorithm is considered the correlation of algorithms and decision variables.

(3) Experiment III: The fuel consumption with three algorithms is compared in different road length.

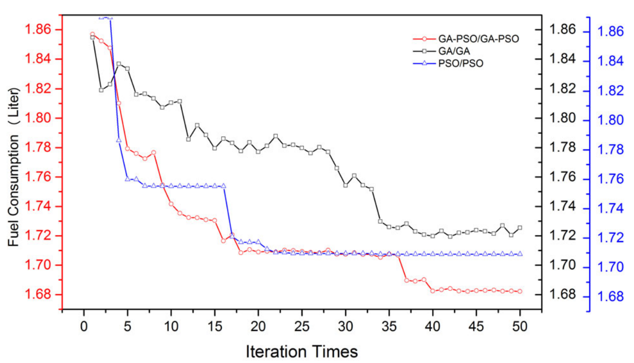
This experiment result shows that the fuel consumption with three algorithms is all linear with added road length because the road distance is linear in the FCCEM. The fuel consumption with GA-PSO/GA-PSO hybrid algorithm is the least in the three algorithms in the same simulation condition, as shown in Figure 8.



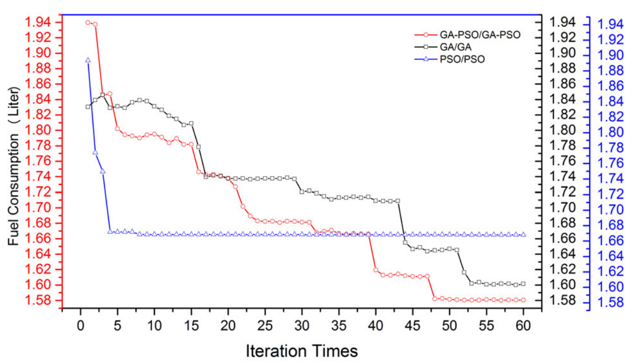
(a) Upper-level iteration times: 30, lower-level iteration times: 20.



(b) Upper-level iteration times: 40, lower-level iteration times: 20

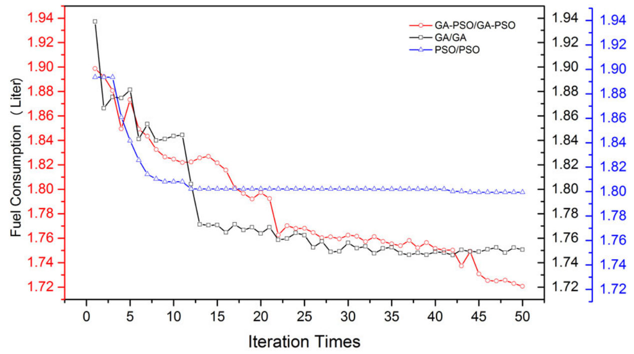


(c) Upper-level iteration times: 50, lower-level iteration times: 20

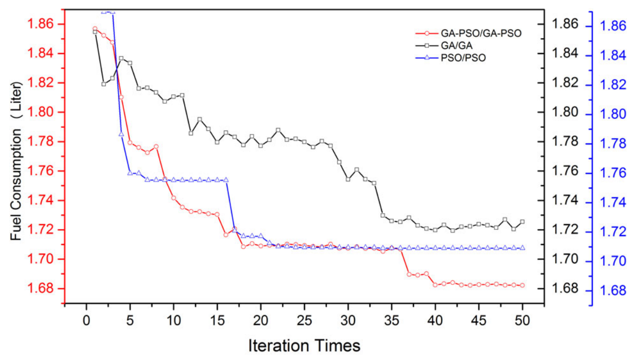


(d) Upper-level iteration times: 60, lower-level iteration times: 20

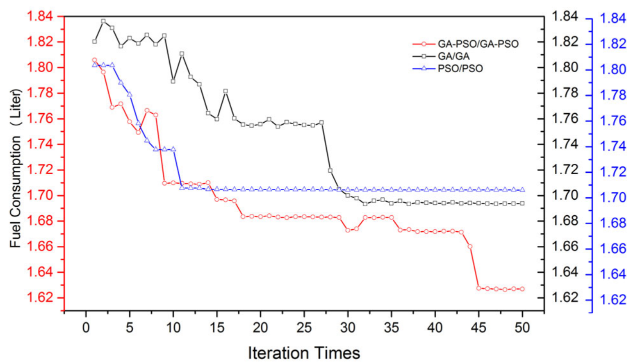
Figure 5. Upper-level iteration times change



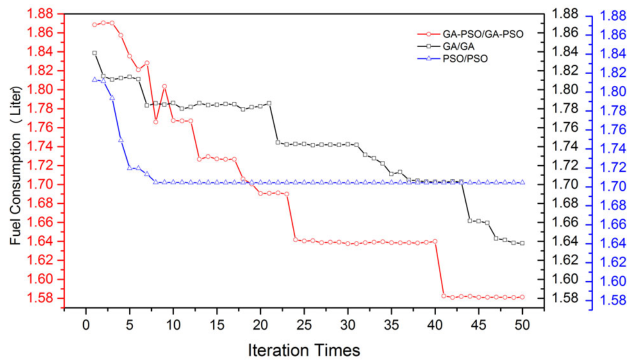
(a) Upper-level iteration times: 50, lower-level iteration times: 10



(b) Upper-level iteration times: 50, lower-level iteration times: 20

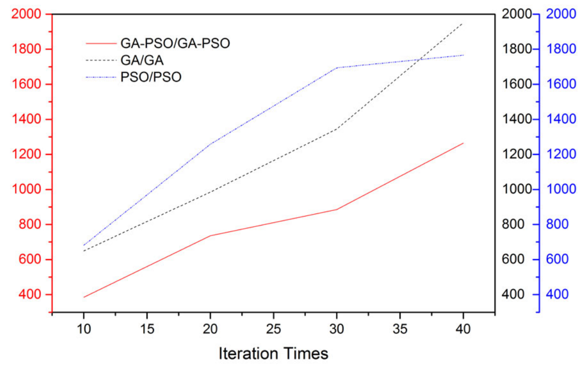


(c) Upper-level iteration times: 50, lower-level iteration times: 30

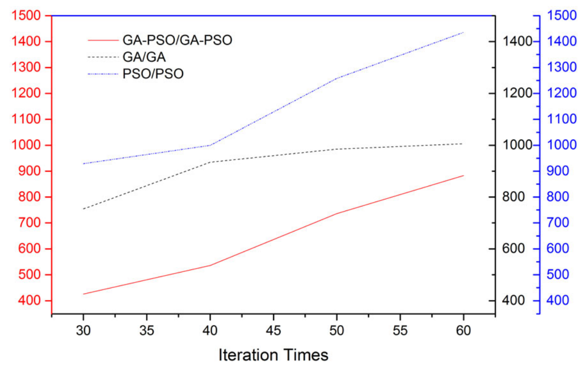


(d) Upper-level iteration times: 50, lower-level iteration times: 40

Figure 6. Lower-level iteration times change

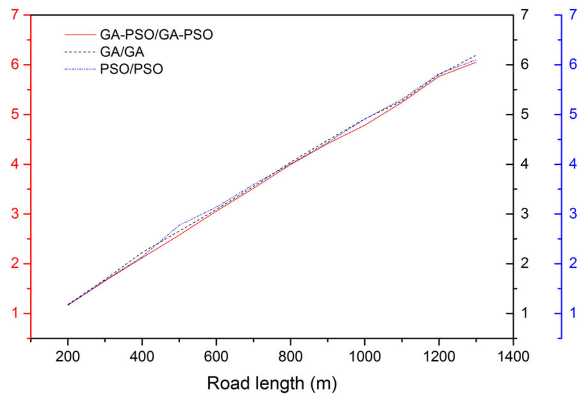


(a) Lower-level Iteration Times: 20

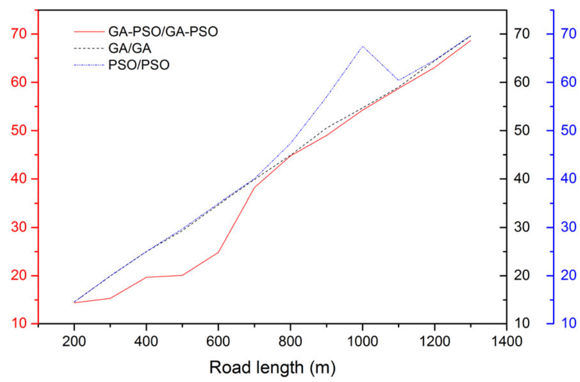


(b) Upper-level Iteration Times:50

Figure 7. Running time comparison with the three algorithms



(a) vph = 100



(b) vph = 1000

Figure 8. Fuel consumption in different road length with three algorithms

(4) Experiment IV: The total consumption with GA-PSO/GA-PSO and GA/GA are compared in different optimization success rate.

The optimization is successful if vehicles move in the optimal speed, and the optimization is failed if vehicles move in a stochastic speed. Figure 9 indicates that the fuel consumptions are both high with two algorithms when no vehicles' motion states are optimized, and the fuel consumption with GA/GA is higher than that with GA-PSO/GA-PSO. The fuel consumption with two algorithms are both declining when optimization success rate becomes higher and higher, and the fuel consumption with GA-PSO/GA-PSO is lower than that with GA/GA. The curve shows that the optimization success rate dramatically affect fuel consumption with both two algorithms.

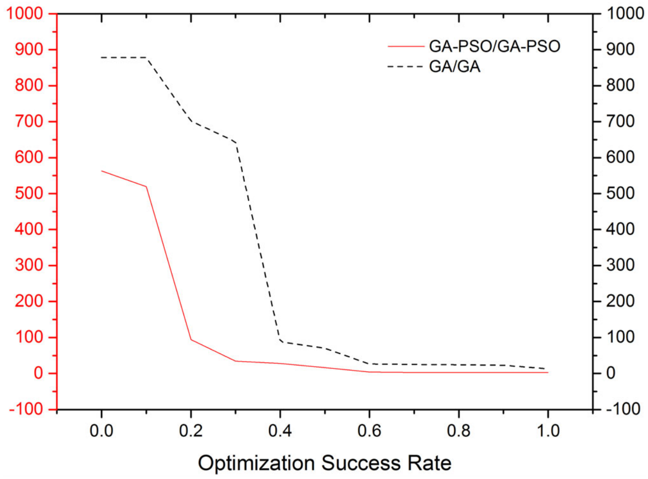


Figure 9. Fuel consumption in different optimization success rate with GA-PSO/GA-PSO and GA/GA

(5) Experiment V: The total fuel consumption with three algorithms are compared and analyzed in 24-hour traffic flow.

The 24-h traffic flow arrival rate information in R1 is shown in Figure 10. Each small square in Figure 10 is a sample to denote the vehicles' arrival rate in R1, i.e., about 11:00 A.M., the vehicles' arrival rate in R1 is 864 vph, and the arrival rate is the same in the opposite direction of R1. The arrival rate in R2 is 432 vph because the traffic flow relationship between R1 and R2 as 2:1.

Figure 11 indicates that, compared with the two no-hybrid algorithms, the proposed BP model with GA-PSO/GA-PSO has better performance in terms of the fuel saving, particularly in the rush hour from about 8:00 A.M. to 9:00 A.M and 5:00 P.M. to 6:00 P.M. This is because the GA-PSO/GA-PSO hybrid algorithm conforms to the characteristic of the decision variables in the BP model. Energy saving with the GA-PSO/GA-PSO compared to PSO/PSO is much more obvious than that with the GA-PSO/GA-PSO compared to GA/GA.

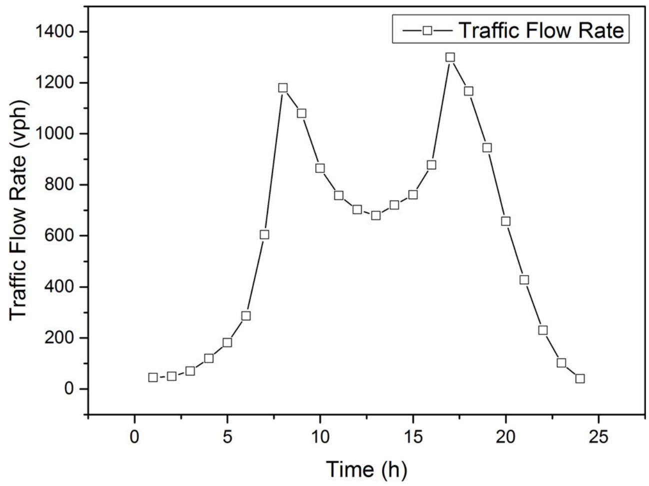


Figure 10. Traffic flow in 24 hours

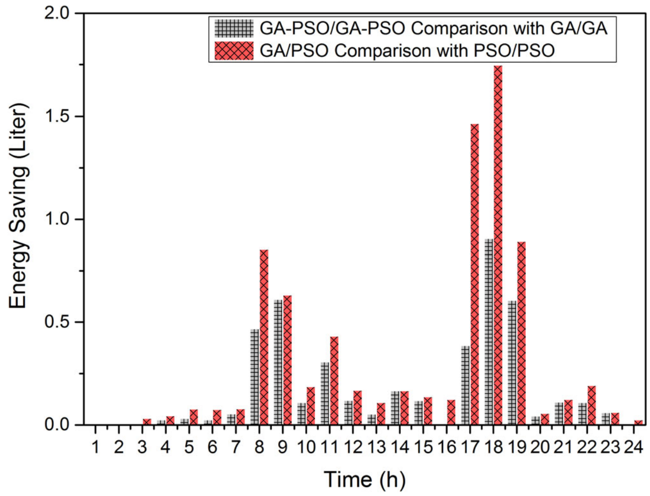


Figure 11. Comparison of fuel consumption with the GA-PSO/GA-PSO hybrid algorithm and other two non-hybrid algorithms

The lower-level model with the single GA in the GA/GA is not suitable because vehicle motion state data as the decision variable of the lower-level model are continuous variables while the chromosome encoding in the GA is a discrete process. On the other hand, the upper-level model with the single PSO in the PSO/PSO is not suitable because traffic signal phasing scheme as the decision variable of the upper-level model is a discrete variable while the update of new particle in the PSO is a successive process. The improved hybrid GA-PSO/GA-PSO algorithm converges more faster and gets better solution because information is exchanged between GA and PSO. So, the performance of the GA-PSO/GA-PSO algorithm in bi-level optimization model is much better than the other two non-hybrid algorithms.

5 Conclusion and Future Works

In this paper, a bi-level optimization model with GA-PSO/GA-PSO hybrid algorithm has been proposed. This control scheme uses the hybrid GA and PSO in both upper-level and lower-level model. The GA is suitable for the discrete decision variable, namely traffic signal phasing scheme, while the PSO is suitable for the successive decision variable, namely vehicle motion state data. The hybrid GA-PSO algorithm obtains the advantages of GA and PSO, and the convergence is faster since the population halve for the hybrid algorithm. Thus, compared with the GA/GA and PSO/PSO, the proposed GA-PSO/GA-PSO performs much better for energy saving and CO_2 emission reduction.

In future works, the bi-level optimization with multi-objective functions will be considered. Furthermore, the BP model extended to more intersections in larger areas will be researched.

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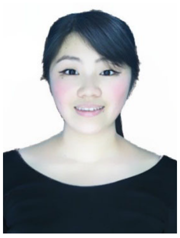
Biographies

Kun Liu is electronic information technology doctoral candidate in Macau University of Science And Technology, Taipa, Macau, China, received the M.S. degree in science and technology from Beijing University of Posts and Communications, Beijing, China, in 2005. Her research interests include Intelligent Transportation Systems, Internet of Things.

Jianqing Li received the Ph.D. degree from Beijing University of Posts and Telecommunications, Beijing, China, in April 1999. From 2000 to 2002, He is a professor. His research interests are network architecture, network protocols, ITS and fiber sensors. He is a senior member of IEEE.



Wenting Li is computer technology doctoral candidate in Macau University of Science And Technology, Taipa, Macau, China, received the M.S. degree in computer technology from Gui Zhou University, GuiYang, GuiZhou, China, in 2010. Her research interests include Intelligent Transportation systems, Database and Data mining technology.

Naixue Xiong is current a full Professor at School of Computer Science, Colorado Technical University, Colorado Spring, CO, USA. He received his both Ph.D. degrees in Wuhan University, and Japan Advanced Institute of Science and Technology, respectively. His research interests include Security and Dependability, Cloud Computing, Networks, and Optimization Theory.