Connectivity-based optimization of vehicle route and speed for improved fuel economy

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ABSTRACT

Traditionally, vehicle route planning problem focuses on route optimization based on traffic data and surrounding environment. This paper proposes a novel extended vehicle route planning problem, called vehicle macroscopic motion planning (VMMP) problem, to optimize vehicle route and speed simultaneously using both traffic data and vehicle characteristics to improve fuel economy for a given expected trip time. The required traffic data and neighbouring vehicle dynamic parameters can be collected through the vehicle connectivity (e.g. vehicle-to-vehicle, vehicle-to-infrastructure, vehicle-to-cloud, etc.) developed rapidly in recent years. A genetic algorithm based co-optimization method, along with an adaptive real-time optimization strategy, is proposed to solve the proposed VMMP problem. It is able to provide the fuel economic route and reference speed for drivers or automated vehicles to improve the vehicle fuel economy. A co-simulation model, combining a traffic model based on SUMO (Simulation of Urban MObility) with a Simulink powertrain model, is developed to validate the proposed VMMP method. Four simulation studies, based on a real traffic network, are conducted for validating the proposed VMMP: (1) ideal traffic environment without traffic light and jam for studying the fuel economy improvement, (2) traffic environment with traffic light for validating the proposed traffic light penalty model, (3) traffic environment with traffic light and jam for validating the proposed adaptive real-time optimization strategy, and (4) investigating the effect of different powertrain platforms to fuel economy using two different vehicle platforms. Simulation results show that the proposed VMMP method is able to improve vehicle fuel economy significantly. For instance, comparing with the fastest route, the fuel economy using the proposed VMMP method is improved by up to 15%.

1. Introduction

Vehicle route planning problem is very important in logistics and transportation. The shortest and fastest route navigations are classic vehicle route planning problems and have been widely used in our daily life through navigation tools. In recent years, due to the rapid development of connected and automated vehicles, more attention has been paid to the vehicle route planning problems (Davis, 2017; Lei et al., 2017). In addition, environmental and energy concerns encourage researchers to develop new energy efficient technologies. Vehicle route planning has the potential to further reduce vehicle fuel consumption and emissions by optimizing vehicle route and speed simultaneously (Lin et al., 2014; Zeng et al., 2016) based on the technological development of vehicle connectivity, a vehicular communication system sharing its real-time information with others through vehicle-to-vehicle, vehicle-to-infrastructure,
vehicle-to-pedestrian, vehicle-to-cloud, and other communication methods (Amadeo et al., 2016; Lu et al., 2014). On the other hand, the improvement of vehicle fuel economy has the potential to reduce transportation cost, especially for heavy-duty trucks (Díaz-Ramírez et al., 2017).

Most of navigation tools provide the shortest and fastest routes for a given origin-destination (OD) pair regardless the trip time. Let $G = (N,W)$ be a directed graph of traffic network with a node set $N$ and an edge weight set $W$, where the edge is a road segment between two neighboring nodes (intersections or junctions) on an actual traffic network. The edge weight $w_{ij} \in W$ is associated with road cost function (e.g. road length and travel time) from node $n_i$ to $n_j \in N$ (Bast et al., 2015; Prins et al., 2014). The shortest (or fastest) route is an ordered sequence of nodes from $N$ with the route length (or travel time) minimized. The edge weights (route length and travel time) are independent and calculated based on traffic network data (e.g. road shape and node position) and traffic flow data (e.g. speed limit and traffic speed) over their edges. Note that the fastest route is the same for different vehicles with the same OD pair and departure time. There are many methods to solve this classic shortest/fastest route problem, such as Dijkstra’s algorithm (Peyer et al., 2009), Bellman-Ford algorithm (Goldberg and Radzik, 1993), A* search algorithm (Zeng and Church, 2009), Floyd-Warshall algorithm (Aini and Salchipour, 2012), and Johnson’s algorithm (Johnson, 1977).

However, the shortest (or fastest) route does not always minimize the fuel consumption (Ahn and Rakha, 2008). As a result, the optimal fuel economic route cannot be solved by above mentioned methods due to the following reasons. First, different from the weighted shortest and fastest route problems, vehicle fuel consumption is not only related to the traffic data but also affected by factors such as vehicle speed, powertrain characteristics, road grade, and driver behavior (Zhou et al., 2016). Second, the edge weights (fuel consumption) are inter-dependent and affected by the information of neighboring edges. For example, the fuel consumption of a conventional ICE (internal combustion engine) powered vehicle over an edge is affected by the gear ratio over the previous edge via the gear-shifting schedule (Miao et al., 2018); and similarly, the fuel consumption of a hybrid electric vehicle (HEV) is affected by its terminal SOC over the previous edge and the information (such as road grade and travel speed) over the current and neighboring edges used in the energy management control strategy (Kamal et al., 2013). Therefore, the route cost is not equal to the sum of weights whose corresponding edges compose the route. Last, the fuel consumption of an individual edge could be negative due to the brake regeneration for an HEV under downhill operations (Jurik et al., 2014), and it worth to note that most of optimization algorithms mentioned above can only deal with positive edge weights. In fact, the vehicle characteristics play an important role in vehicle route planning problems, even for the fastest route. For example, a small passenger car and a heavy-duty commercial truck could have different fastest routes due to the difference in vehicle acceleration/deceleration performance and related speed limit. The existing on-board powertrain controllers and navigation tools cannot optimize the route based on both traffic data and vehicle characteristics. Fortunately, the rapid development of vehicle connectivity makes it possible in near future to optimize vehicle fuel economic route using both traffic data and vehicle characteristics (Amadeo et al., 2016; Lu et al., 2014).

Fuel economy related vehicle route planning research got started in the past decades, such as eco-routing navigation (Boriboonsomsin et al., 2012; Lang et al., 2015; Zeng et al., 2016), green vehicle routing problem (Erdogan and Miller-Hooks, 2012; Tiwari and Chang, 2015; Turkensteen, 2017; Koç and Karaoglan, 2016; Leggiieri and Haouari, 2017; Montoya et al., 2016; Bruglieri et al., 2016), and pollution vehicle routing problem (Ehmke et al., 2016; Tajik et al., 2014; Demir et al., 2012; Jabali et al., 2012; Bekta and Laporte, 2011). In these literature, authors try to minimize vehicle fuel consumption and/or emissions through the route optimization. In general, the proposed fuel economic route is generated in three steps. First, a cost function is established to evaluate fuel consumption and/or emissions. As mentioned above, the fuel consumption is affected by many factors and it is difficult to calculate it accurately in real-time. As a result, simplified fuel economy models are proposed to estimate fuel consumption based on vehicle dynamics, including instantaneous fuel consumption model, mean-value phenomenological model, engine-based model, vehicle-based model, comprehensive modal emission model (CMEM), and invariant models (Zhou et al., 2016; Turkensteen, 2017; Golec,biowski and Stoek, 2014). The CMEM is the most widely used model based on fuel rate modules, vehicle speed, engine power and speed. Second, a mathematical model based on the directed graph and a mixed integer linear program (MILP) (Erdogan and Miller-Hooks, 2012; Mancini, 2017; Bruglieri et al., 2016) is formulated for the route planning problem. Third, the fuel economic route is solved using different methods, such as heuristic algorithm (Prins et al., 2014; Erdogan and Miller-Hooks, 2012; Montoya et al., 2016; Koç and Karaoglan, 2016; Demir et al., 2012), robust optimization (Tajik et al., 2014), genetic algorithm (Tiwari and Chang, 2015; Lau et al., 2010), particle swarm optimization approach (Gong et al., 2012), and ant colony system (Androutsopoulos and Zografos, 2017). The optimized results show that the fuel economic route has the potential to reduce fuel consumption and emissions with fixed traffic (vehicle) speed. In addition, some other related vehicle route planning problems based on HEVs (Mancini, 2017) and electric vehicles (Felipe et al., 2014; Schneider et al., 2014; Hiermann et al., 2015) were proposed for the environment improvement in recent years. Demir et al., 2012; Franceschetti et al., 2013; Barth and Boriboonsomsin, 2009; Huang et al., 2017; and Tas et al., 2014 studied the speed optimization problem with a given route and trip time constraint and showed that the speed optimization was able to decrease fuel consumption over a fixed route with a given trip time constraint. It indicates that vehicle fuel economy could be further improved by combining route planning and speed optimization into a co-optimization problem.

Therefore, a vehicle macroscopic motion planning (VMMP) problem is formulated to improve vehicle fuel economy by providing the economic route and speed for a given origin destination pair with an expected trip time. The VMMP problem is defined as a global co-optimization problem to find the economic vehicle route and speed profile simultaneously that minimize the cost function (e.g. fuel consumption) from origin to destination over a traffic network. This is motivated by the fact that vehicle route and speed are coupled in the fuel economy optimization problem. Considering the dependency of neighboring edges, a co-optimization method containing two coupled genetic algorithm (GA) optimization processes is proposed to optimize vehicle route and speed. In practice, vehicle route is not time-varying due to traffic rules and may remain unchanged before approaching an incoming intersection, therefore, an adaptive real-time optimization strategy is designed to update the route and speed under different rates for online
applications. The proposed VMMP method could be applied to human-driven, partial-automated, and automated vehicles. For human-driven vehicles, it could provide vehicle fuel economy route and reference speed for driver; for partial-automated vehicles with adaptive cruise control (ACC) system, the optimized speed can be used as the target speed for ACC system; and for automated vehicles, the economic route and speed optimized by the VMMP method can be used as the reference route and speed for vehicle motion control system to realize autonomous driving for improved fuel economy. Note that the route and speed of automated vehicles are planned by decision making system and controlled by motion control system automatically (Li et al., 2017).

The main contribution of this paper is threefold. First, a novel extended vehicle route planning problem, called VMMP, is proposed to improve vehicle fuel economy by optimizing vehicle route and speed simultaneously based on both traffic data and powertrain characteristics, and it is useful to reduce both emissions and transport cost due to improved fuel economy. Second, a GA based co-optimization method is proposed to solve the proposed VMMP problem for the fuel economic route and reference speed, and a real-time adaptive optimization strategy is also developed for practical applications. Last, the proposed VMMP method makes eco-driving (Díaz-Ramírez et al., 2017; Jamson et al., 2015; Fors et al., 2015) easier by providing the economic route and associated reference speed for the driver. Note that the reference route and speed can also be used in autonomous vehicles directly.

This paper is organized as follows. The mathematical formulation of the proposed VMMP problem is presented in Section 2. In Section 3, a GA based co-optimization method is proposed to obtain the economic route and speed for the VMMP problem. An adaptive real-time optimization strategy, along with the penalty model of traffic light, is developed for real-time applications. Section 4 is devoted to the development of simulation models including a traffic model in SUMO (Simulation of Urban MOBility) and a forward powertrain model in Matlab/Simulink. Four simulation studies are conducted to evaluate the proposed VMMP method and their associated results are presented and compared in Section 5. Section 6 adds some conclusions.

2. Mathematical formulation of the VMMP problem

For a given OD pair and an expected trip time, the goal of the proposed VMMP problem is to improve fuel economy by optimizing vehicle route and speed simultaneously. Note that this is a multi-variable global optimization problem and this section describes the mathematical formulation of the proposed VMMP problem.

2.1. Powertrain-based fuel consumption model

The fuel consumption calculation is one of the most important modeling tasks for the VMMP problem. Comparing with the shortest and fastest routes, the cost function (fuel consumption) of the VMMP problem is much more complicated since it is affected by many factors (see Zhou et al., 2016), but it can be analyzed based on vehicle powertrain dynamics (Miao et al., 2018).

For a conventional ICE vehicle, the fuel consumption FC (g) can be expressed as

$$FC = \int_{t_0}^{T} \gamma g_e(t) T_r(t) n_t(t) dt$$

where $\gamma$ (g/kW h) is the rate of fuel consumption obtained from the engine map based on current engine speed $n_e$ (r/min) and torque $T_r$ (N m); $\gamma = 1/(9549 \times 3600)$ is a coefficient for unit conversion; and $T$ (s) is the trip time. For the VMMP problem, the trip time can be estimated by the speed and associated sensor positions along the road.

$$T = \sum_{k=1}^{M_s} \frac{\Delta s(k)}{v(k)}$$

where $M_s$ is the total number of sensor (such as the speed sensor, counter, and inductive loop detector) located along the route (r); $v(k)$ is vehicle speed at sensor location $k$; and $\Delta s(k)$ is the distance between sensor locations $k$ and $k + 1$.

For conventional ICE vehicles, engine power is transmitted to driven wheels through torque converter/clutch, transmission, final drive, and drive axle. The powertrain dynamics can be expressed as

$$\delta \dot{m_i}(k) = \frac{i_g(k) \eta_i(T_i(k))}{R} \left( mg \dot{\delta}(k) + 0.5 C_d \rho A v^2(k) \right)$$

$$n_t(k) = \frac{30 i_g(k) \eta_i}{\pi R} v(k)$$

$$i_g(k + 1) = g(ge(k), v(k), T_r(k))$$

where $m$ is vehicle mass; $\delta$ is mass factor including an equivalence coefficient of rotating mass; $\dot{v}$ is vehicle acceleration calculated by (6) for known speed profiles; $\beta$ is a road coefficient combining road grade ($\delta$) and rolling resistance coefficient ($\zeta$) (see Eq. (7) and Miao et al., 2018); $C_d$ is drag coefficient; $\rho$ is air density; $A$ is vehicle frontal area; $R$ is vehicle wheel radius; $\eta_i$ is driveline efficiency; $i_g$ is transmission gear ratio, where gear number $ge$ is determined by a gear-shifting schedule; and $i_0$ is vehicle final ratio.

$$\dot{v}(k) = \frac{v^2(k + 1) - v^2(k)}{2 \Delta s(k)}$$

$$\beta(k) = \zeta(k) \cos \delta(k) + \sin \delta(k)$$
Based upon Eqs. (2)–(6), the fuel consumption model can be simplified as a function of vehicle speed \((v)\), road coefficient \((\beta)\), and route length \((s)\).

\[
FC = \sum_{k=1}^{M} f(\beta(k), v(k)) \frac{1}{v(k)} \Delta s(k)
\]  \hspace{1cm} (8)

Note that, the road grade can be calculated by the road altitude and distance obtained from the geographic information system (GIS) and global positioning system (GPS) through the vehicle connectivity (Barth and Boriboonsomsin, 2009). And then, vehicle route and speed along the route are remaining unknowns for fuel consumption calculation and they are optimization variables for the proposed VMMP problem.

2.2. VMMP problem formulation

Similar to other vehicle route planning problems, the traffic network can be simplified into nodes and edges (Bast et al., 2015; Ehmke et al., 2016). The nodes represent road intersections or junctions and the edges are road segments connecting the neighboring nodes. For a given OD pair, let \(N\) be the number of feasible edges located between the origin and destination positions. That is, the feasible edge has at least one node inside the rectangular area, and the origin and destination pair forms the pair of diagonal vertexes. Define a binary matrix \(\Phi = [\phi_{ij}]_{1 \times N} \) representing connections among them. Normally, the edge of origin is set to 1 and the edge of destination is \(N\). Entry \(\phi_{ij}\) is a binary variable expressing the connection from edge \(i\) to \(j\), where \(\phi_{ij}\) equals to 1 if a vehicle could drive from edge \(i\) to \(j\) directly, and otherwise, it equals to 0. Note that \(\phi_{ij}\) is set to 0 in this study. The route \(r\) from origin to destination consists of some edges with their associated connection variables \(\phi_{ij}\) equal to 1.

The input signals of VMMP contain current traffic flow data, speed limit, sensor location IDs and positions, traffic light positions and timing, etc. These data can be collected based on road sensors, navigation tools, and vehicle connectivity. They can also be classified and stored by nodes and edges. For example, the current traffic speed and associated sensor positions on edge \(i\) can be expressed as

\[
v^c_i = [v^c(1) v^c(2) ... v^c(M_i)]
\]  \hspace{1cm} (9)

\[
s_i = [s(1), s(2) ... s(M_i)]
\]  \hspace{1cm} (10)

where \(M_i\) is the number of sensor locations on edge \(i\); superscript \(C\) indicates the current speed. Note that speed \(v^c(k), k \in [1, M_i]\) is the actual traffic speed provided by the sensor at position \(s(k), k \in [1, M_i]\) at current time (Boriboonsomsin et al., 2012). Note that speed \(v^c(k), k \in [1, M_i]\) is an averaged speed (mean value over an update sensor period) for all lanes at the associated sensor position \(s(k), k \in [1, M_i]\).

In addition, let \(S, V^c, V^u, V^l\) represent vectors of sensor position, current traffic speed, upper and lower speed boundaries on route \(r\), respectively. Note that \(S, V^c, V^u, V^l\) have the same order and match with the sensor locations along route \(r\). Note that the vehicle route is an ordered sequence of some edges from \([1, 2, ..., N]\), which are formulated using their connection variables \(\phi\).

For a given OD pair, the trip fuel consumption is a function of the selected route and vehicle speed along the route; see (8). Therefore, a global optimization problem, called the vehicle macroscopic motion planning (VMMP) problem, is defined to find the best fuel economic route \((r^*)\) and reference speed vector \((V^*)\) that minimize the trip fuel cost function \((J)\) for a given OD pair and expected trip time. Note that the resulting reference speed is optimal only for the selected route and the optimal VMMP solution is corresponding to the given expected trip time.

2.2.1. Vehicle macroscopic motion planning problem

Find both vehicle route \(r^*\) and associated reference speed \(V^*\) that minimize the following cost function \((J)\) for a given origin-destination pair and expected trip time \(T_e\)

\[
J = \sum_{i=1}^{N} \sum_{j=1}^{N} \phi_{ij} \left( \sum_{k=1}^{M} f(\beta(k), v(k)) \frac{1}{v(k)} \Delta s(k) \right)
\]  \hspace{1cm} (11)

subject to the following constraints

\[
\sum_{j=1}^{N} \phi_{ij} \leq 1 \quad \forall i \in [1, N]
\]  \hspace{1cm} (12)

\[
\sum_{i=1}^{N} \phi_{ij} \leq 1 \quad \forall j \in [1, N]
\]  \hspace{1cm} (13)

\[
\sum_{j=1}^{N} \phi_{ij} = 1 \quad \sum_{i=1}^{N} \phi_{iN} = 1
\]  \hspace{1cm} (14)
\[ \sum_{i=1}^{N} \phi_{in} + \sum_{j=1}^{N} \phi_{nj} = \begin{cases} 0, & \sum_{j=1}^{N} \phi_{nj} = 0 \quad \text{or} \quad \sum_{i=1}^{N} \phi_{in} = 0 \\ 2, & \sum_{i=1}^{N} \phi_{in} = 1 \quad \text{or} \quad \sum_{j=1}^{N} \phi_{nj} = 1 \end{cases}, \quad \forall n \in [2,N-1] \]  

(15)

\[ \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \frac{1}{v(k)} \Delta \sigma(k) \leq T_E \]  

(16)

and in addition, at each sensor location \((k)\), the vehicle speed \(v(k)\) is subject to powertrain dynamic constraints (3)–(6) and the associated traffic lower \(v^L(k)\) and upper speed limits which are the smaller speed between the current \(v^C(k)\) and the highest one \(v^U(k)\), respectively, below

\[ v^L(k) \leq v(k) \leq \min(v^L(k), v^U(k)). \]  

(17)

Note that constraints in (12) and (13) make sure that the feasible edges for the given OD pair are travelled only at most once; constraints in (14) provide the initial and terminal conditions; constraints in (15) show that if one edge is selected, there exist both entering and departure edges to make sure that both edges are connected each other. As a result, a one-way continuous route from initial to terminal edge can be formed (Ahn and Ramakrishna, 2002). Constraints in (16) make sure that the trip time form O to D does not exceed the expected one; and constraints in (17) show that the vehicle should follow the traffic flow and obey the traffic rules.

3. Heuristic method to solve the VMMP problem

3.1. GA based co-optimization method

After the mathematical model of VMMP is obtained, the next step is to solve it for the economic route and speed profile. This is a global optimization problem with two variables, various equality and inequality constraints. For global optimization algorithms, GA is widely used to generate high-quality solutions for optimization and search problems, and it was used to solve the related vehicle route planning problems (Tiwari and Chang, 2015; Lau et al., 2010; Ahn and Ramakrishna, 2002). GA is an iterative procedure relying on bio-inspired operators such as selection, mutation, and crossover; see Fig. 1.

Usually, the initial population is generated randomly, distributing uniformly over the possible solution set. In each iteration, the individuals of current population are evaluated by fitness (or cost function) values in an optimization problem. The best individuals are selected from the current (parent) population to produce the next generation. The mutation and crossover are two basic genetic operators for generating the next population, where the mutation introduces new characteristics into selected parent individuals by altering one or more gene values and the crossover produces a new individual from more than one parent individuals by displacing some gene values of an individual from others.

The fuel economic route and speed profile are a pair of coupled binary vector and positive real array, respectively. The dimension and boundary of speed depend on its corresponding route. The economic speed profile is effective for its corresponding route and has no physical meaning for other routes. In this section, a GA based method is proposed to co-optimize vehicle route and speed profile simultaneously; see Fig. 2.

Note that \(k_r\) and \(k_r\) are iteration indices of speed and route, respectively; and (18) below is the terminal criterion

\[ r^*(k_r) = r^*(k_r-1) \& \ U^r(k_r) - J^r(k_r-1) < \sigma \]  

(18)

Fig. 2 is self-explanatory and it can be seen that both GA iteration processes are embedded together. The outer iteration loop is used for route optimization and the inner one is for speed optimization. The inputs to speed optimization are provided by the selected

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**Fig. 1.** Basic iterative process of genetic algorithm.

**Fig. 2.**
route individuals (see steps S6 and S7 in Fig. 2), and the fuel consumption of the economic speed profile is used as input to the route optimization (see S11 in Fig. 2). The route fuel consumption ($J_r$) is used to determine if the iteration is converged or not. The population initializations (steps S3 and S6) and genetic operational processes (steps S10 and S14) are very important in this algorithm. Detailed descriptions for S3 and S14 are provided in this paper. Steps S6 and S10 are similar to S3 and S14, respectively, and can be carried out in the same manner. Note that the proposed method in Fig. 2 cannot guarantee that the economic route and speed are optimal solutions. Because the genetic algorithm is heuristic, the terminal criterion in (18) does not guarantee optimality. However, genetic algorithm is globally convergent (Rudolph, 1994) and its solution approaches to the optimal one as $\sigma$ decreases.

Detailed step S3 (route population initialization $P_r(1)$) is provided below.

(a) Initialize the route population size ($l_{rp}$), group ($l_{rg}$), and select sizes ($l_{rs}$) for tournament selection in step S13, mutation ($l_{rm}$) and crossover size ($l_{rc}$) used for generating the next population in step S14, and iteration number upper bounds $l_i$ and $l_o$ for iteration process ($k_r = k_r + 1$) and genetic operation in step S14, respectively, to avoid infinity loop.

(b) Select a random edge ($n$) and create two partial routes (from 1 to $n$ and from $n$ to $N$) using constraints in (12)–(15) (see Ahn and Ramakrishna, 2002 for details);

(c) Combine these two partial routes into one route ($r$) from edge 1 to $N$ by merging two vectors (partial routes from step (b)) into one and removing the repeated edge $n$;

(d) Check the route trip time ($T_r$) by calculating the minimum $T_r$ using (2), where $v \in V_C$. If $T_r \leq T_E$, store route $r$ into the initial population $P_r(1)$; otherwise, eliminate route $r$ and repeat steps (b), (c), and (d);

(e) Repeat steps (b), (c), and (d) until the size of $P_r(1)$ is increased to $l_{rp}$. Then set $k_r = 1$ and go to next step S4.

Step S14 (mutation and crossover) is used to generate new population ($P_r(k_r + 1)$) through mutation and crossover based on the selected parent individuals ($P_r^*(k_r)$) as below.

(a) Initialize the random route size ($l_{rp}$) and offspring number of each parent individuals according to $l_{rm}$ and $l_{rc}$. Note that the next
population $P(1, k + 1)$ is made up of random routes (size $l_p$), selected $P^1(1, k)$ (size $l_p$), and their offspring routes (size $l_{p(1)}=l_{p(2)}-l_p$).

(b) Select two random edges ($n_1$ and $n_2$) in the parent route from selected ones $P^1(1, k)$;

c) Mutation: create a new partial route from $n_1$ to $n_2$ using the constraints (12)–(15) (see Ahn and Ramakrishna, 2002 for details), and replace the partial route of parent individual to generate a new one;

d) Crossover: find same edges $W$ from two parent routes ($n_1$ and $n_2$). Then select a random edge ($n$) from $W$ and generate a new route by combining a partial route for edge 1 to $n$ in $E_1$ and a partial route for edge 2 to $N$ in $E_2$;

e) Check the inequality and trip time limit. If the offspring route is equal to the parent route or $T_r > T_E$ (see step (d) in S3), give it up and repeat steps (b), (c)/(d), and (e); otherwise, store it into $B(k, 1)$;

(f) Repeat steps (b), (c), (d), and (e) until the size of $P(1, k + 1)$ is increased to $(l_{p(1)}-l_{p(2)}-l_p)$ and generate $l_{p(2)}$ random routes using the above method (step S3).

Note that the proposed adaptive real-time optimization strategy (Fig. 2) is designed to reduce computational cost for real-time applications. It can be observed that there is no multiplication in the outer iteration loop, and only several multiplications in (2), (3), (4), (6), and (8) at each sensor location are required for the inner iteration loop. Therefore, the algorithm is simple enough for real-time implementation and can be handled with the existing vehicle on-board real-time microprocessors.

The premature convergence is a common problem of GA. It means that a population for an optimization problem converged too early, resulting in a suboptimal solution. Several strategies can be used to avoid premature convergence (Pandey et al., 2014). In this paper, the random offspring generation (steps S10 and S14) and tournament selection (steps S9 and S13) are used to avoid it. In addition, large population size can be used to avoid premature convergence with the penalty of computational load. Therefore, a primary selection based on evaluation 1 (see step S4 in Fig. 2) is utilized to reduce computational load. The approximated cost function ($J_k$) is calculated based on an ideal mile-per-gallon (MPG) model. It is a speed-fuel lookup table calculated off-line based on the given powertrain model (Bekta and Laporte, 2011). Three speed profiles are used for $J_k$ calculation: upper speed boundary, lower speed with $T_E$, and economic speed according to the ideal MPG model. The cost function $J_k$ is the minimum of three costs.

3.2. Optimization for real-time implementation

3.2.1. Adaptive real-time optimization strategy

In practice, the route is not time-varying and usually remains unchanged for a long time, especially under highway driving. An adaptive real-time optimization strategy is proposed to update the economic route and speed with different update rates, where the speed profile is updated in the same rate as data sampling one, and the route is only updated several seconds before approaching the closest intersection or junction since it is assumed that the route can only be changed at the intersection or junction (the end of an edge or the beginning of next one). Note that the length of edge is not fixed since it is dependent on the real traffic network and varies based on the locations of intersections and junctions. Then a mathematical formulation is generated for updating the route.

$$\begin{align*}
\sum_{j=1}^{N} \phi_{ij} & \geq 2 \\
\Delta L & \leq 300 \\
\mu & = 0
\end{align*}$$

(19)

where $\sum_{j=1}^{N} \phi_{ij} \geq 2$ ensures that the current edge ($k$) has more than one outputs at the end of an edge; $\Delta L$ is road distance between the current position and the node at the end of edge; and $\mu$ is a defined route optimization flag with the default value of 0. When a vehicle is driving on a new edge, $\mu$ is set to 0; and when Eq. (19) is satisfied and the economic route is updated for the current edge, $\mu$ is set to 1.

In addition, a modified parallel GA optimization method is proposed for the speed optimization; see Fig. 3. Different from the co-optimization structure in Fig. 2, the speed population is generated in two ways. One is to obtain speed vectors based on individual mutations of the optimized speed profile in the last step and the other is to generate random speed vectors using the same approach as the one used in the co-optimization method. These two speed populations are evaluated together but iterated independently to avoid premature convergence to the previous optimized result. Note that the two iteration processes are carried out at the same time.

Therefore, in practice, vehicle route and reference speed profile are optimized simultaneously using co-optimization method in Fig. 2 when the constraint (19) is met; otherwise, the economic route remains unchanged and the reference speed profile is updated at a fixed update rate using the modified parallel GA in Fig. 3.

3.2.2. Penalty model for traffic light

In actual traffic environment, it is hard to avoid random situations, especially for traffic light. The trip time and fuel consumption may be different from the optimized ones. Therefore, the proposed VMMP method is modified by adding a penalty model of traffic light. The actual trip time can be divided into moving time duration and waiting duration for green light. And the time limit for vehicle route and speed optimization should be the moving time duration defined as

$$T_{opt} = T_r - \sum_{k_i=1}^{N_1} T_{wait}(k_i)$$

(20)

where $T_{opt}$ is the actual trip time limit for route and speed optimization; $T_{wait}(k_i)$ is the waiting time duration at an intersection with
traffic light $k_i$; and $N_t$ is the total number of traffic light along the route.

The waiting time duration is defined as a random variable depending on your arrive time and current traffic light duration. It is hard to build an accurate model for calculating $T_{wa}$ in this paper, we use a probability model below to estimate $T_{wa}$.

$$T_{wa} = \sum_{i=1}^{t_i+t_y} p \cdot t_{wa}(i)$$

(21)

$$P = \frac{1}{T_g + T_y + T_r}$$

(22)

where $T_g, T_y$, and $T_r$ are time duration of green, yellow, and red light, respectively. Note that other color phases, like flashing yellow and red, are distributed to the yellow phase in this paper. The traffic light timing and duration can be collected through the V2I (vehicle-to-infrastructure) communication.

In addition, the fuel consumption is also affected by traffic light. The vehicle needs to decelerate and then accelerates to the initial speed when the traffic light turns to green from red, leading to increased fuel consumption. The fuel consumption with traffic light can be modified as

$$F_{mod} = F_{opt} + \sum_{k=1}^{N_t} p_t(k_i)(F_g(k_i)-F_g(k_j))$$

(23)

$$p_t = \frac{T_r + T_y}{T_g + T_r + T_y}$$

(24)

$$F_t = \int_{t_0}^{t_1+t_{dec}} f(\beta(t),\nu(t))dt$$

(25)

$$F_g = f(\beta(t_0),\nu(t_0)) \cdot (t_{dec} + t_{acc})$$

(26)

where $F_{mod}$ is the modified fuel consumption; $F_{opt}$ is fuel consumption without traffic light; $p_t$ is the stopping probability due to traffic light; $F_t$ is the extra fuel consumption due to vehicle decelerating to stop and accelerating to the initial reference speed; $F_g$ is the fuel consumption when traffic light is green; $t_0$ is time for vehicle to start decelerating; $t_1$ is time for vehicle to start accelerating; $t_{dec}$ is decelerating time duration from the initial speed $\nu(t_0)$ to 0; and $t_{acc}$ is accelerating time duration from 0 to the initial speed $\nu(t_0)$.

4. Co-simulation model

4.1. Traffic model in SUMO

There are several software platforms for traffic modeling, e.g. SUMO, Visim, Prescan, and so on (Ratrout and Rahman, 2009). The traffic model for the VMMP problem shall provide both macroscopic (e.g. traffic speed, etc.) and microscopic traffic data (e.g. vehicle speed and position, traffic light information, etc.). The SUMO is a better choice and the other two platforms (Visim and
Prescan) are good only for the microscopic traffic modeling. A real traffic network between Novi, MI and Southfield, MI is used for traffic modeling. The required map is downloaded from OpenStreetMap, firstly, and then, converted to the SUMO network model with modifications using JOSM (Java OpenStreetMap) editor. After that, the traffic flow and other model parameters are generated and set using SUMO applications. The detailed modeling process can be found in reference (Krajzewicz et al., 2012). The traffic model in SUMO is shown in Fig. 4.

### 4.2. Forward powertrain model in Matlab/Simulink

Two powertrain models are used in this research and they are backward and forward powertrain models. The former is used to calculate the cost function (see Section 2), and the latter is used to track the fuel economic speed profile in simulations. The main difference between the two models is the driver model. The backward model calculates the fuel consumption based upon the given vehicle speed profile (speed profiles in Fig. 2) so that the driver model is not required. But for real-time simulations, the driver model (or pedal controller for automated vehicle) is required to follow the reference speed. The forward powertrain model is developed in Simulink (see Fig. 5), where the driver model consists of two PID (proportional integral derivative) control modules. One is for acceleration pedal control and the other is for brake pedal control. The DCT (dual-clutch transmission) controller has a two-parameter gear-shifting scheduling strategy and a gear-shifting controller. Note that the fuel consumption obtained from backward and forward powertrain models are different and errors between these two models are discussed in the next section.

Note that in Fig. 5, $\alpha$ is throttle position; $T_e$ and $N_e$ are engine output torque and speed, respectively; $T_t$ and $N_t$ are transmission output torque and speed, respectively; $v$ and $v^*$ are actual and reference speed, respectively.

### 4.3. Co-simulation model

Combining the traffic and powertrain models, a co-simulation model is obtained; see Fig. 6. The connection between SUMO and Matlab/Simulink models is realized by TraCI4Matlab, an API (application programming interface) developed in Matlab that allows the communication between any applications developed in Matlab language and the urban traffic simulator SUMO. TraCI4Matlab allows controlling SUMO objects such as vehicles, traffic light, and junctions. The simulation steps of both traffic and powertrain models should be the same and are set to be 0.01 s in this study. The sensor update period in the traffic model is set to be 1 s. Note that $\Delta v$ in Fig. 6 is the speed modification to have a safety distance to the vehicle in front.

### 5. Simulation validation and result analysis

This section studies fuel economy improvement for ICE vehicles using the proposed VMMP method. First, a simulation study
under ideal traffic environment with certain assumptions is conducted to compare the fuel consumption using the proposed VMMP method, traditional route or speed optimization, and the fastest route without optimization. Second, traffic light are added to the co-simulation model to validate the proposed VMMP method with the penalty model of traffic light. Third, traffic jam is added to the co-simulation model to validate the proposed VMMP method including the adaptive real-time optimization strategy. At last, two vehicle platforms are used to study the effect of vehicle powertrain type on fuel economy.

5.1. Simulation study under ideal traffic environment

Similar to other vehicle route planning problems, the VMMP is a macroscopic optimization problem. It focuses on a long term travel and tries to improve the global (or trip) fuel economy. Some microscopic vehicle movements, such as vehicle following and lane changing, are ignored. Therefore, we use certain assumptions and setups to build an ideal traffic environment for validating the proposed co-optimization method.

The following assumptions are made for co-optimization model: (a) traffic light is assumed to be green so a vehicle can travel through intersections without braking and waiting; (b) there is no traffic jam and surrounding vehicles to keep safety distances for the studied vehicle; and (c) the lane changing does not increase route length and fuel consumption.

Different from the other related research, the proposed VMMP problem takes vehicle speed optimization into account. Firstly, a speed-oriented simulation on fixed routes with different trip time limits is conducted. The OD pair is shown as OD1 in Fig. 7. The test routes are set to be the shortest (RS1) and fastest routes (RF1), respectively. The expected trip time ($T_E$) are set to be 1.25 and 1.5 times of the route's minimum trip time ($T_{min}$), respectively.

Fig. 8 shows reference and tracking speed profiles on the fastest and shortest routes, respectively. The speed trajectories $V_{SI}$ and $V_{FI}$ are unoptimized vehicle speed created by the default PID controller in SUMO. $V_{SIII}$ and $V_{FIII}$ are optimized vehicle speed profile for 1.25$T_{min}$ using the proposed co-optimization method. $V_{SIV}$ and $V_{FIV}$ are optimized vehicle speed profile for 1.5$T_{min}$. Note that there are a few low speed locations at around 2 km, 6 km in Fig. 8 and 15 km in Fig. 8(b). These are locations where the vehicle needs to decelerate to make a turn safely. From Fig. 8, it can be seen that the forward powertrain model is able to track the reference speed well and the optimized reference speed is reduced when the expected trip time is increased. The detailed fuel consumption and trip time are shown in Table 1.

The notations of route and speed in Table 1 are corresponding to these in Figs. 7 and 8. $T_E$ is the expected trip time and $T_S$ is the simulated one. $\Delta F$ is the fuel consumption difference between unoptimized (‘Fast’ and ‘Short’ groups in Table 1) and optimized speed. Note that $T_E$ in ‘Fast’ and ‘Short’ groups are the minimum trip time calculated by route length and current traffic speed based on (2). Because of the required turning, $T_S$ are slightly larger than $T_E$ for these two groups. From Table 1, it can be seen that as expected speed

![Fig. 6. Simulation architecture using SUMO and Matlab/Simulink.](image_url)

![Fig. 7. Route trajectories for OD1 and OD2 under ideal traffic environment.](image_url)
optimization is able to decrease fuel consumption by about 10%. The simulated time durations of ‘Eco S-I’, ‘S-II’, ‘F-I’, and ‘F-II’ groups are smaller than their expected trip time. That is, the vehicle will arrive at the destination D1 within the given trip time limit. This indicates that the proposed speed optimization is able to improve the fuel economy within the expected trip time.

As mentioned above, both backward and forward powertrain models are used in this simulation study. It may lead to different fuel consumption and trip time between the optimized solution and simulation result. In addition, the reference vehicle speed and tracked speed in simulation using the forward powertrain model could also be different. Simulated fuel consumption and trip time could be slightly different due to both factors; see Table 2.

Note that in Table 2, \( \Delta T = \frac{T_O - T_S}{T_O} \times 100\% \) and \( \Delta F = \frac{F_O - F_S}{F_O} \times 100\% \); \( T \) and \( F \) are trip time and fuel consumption, respectively; subscripts \( O \) and \( S \) represent the optimized and simulated results, respectively. From Table 2, it can be seen that there exist fuel consumption and trip time errors, however, they are less than 0.5%. Comparing with the results in Table 1, the errors are small enough and have almost no effect on the optimization results. On the other hand, in practical applications, other errors could be even larger than these due to the difference in driving behaviors.

Next, a simulation study for the proposed GA based co-optimization of vehicle route and speed is carried out. In this simulation study, only origin-destination and corresponding trip time limit are given. In order to have a fair comparison, the trip time limit is set to be the same as those used in above speed-oriented simulations. In addition, OD2 (see the second OD pair in Fig. 7) is added for the study. The simulation results are provided in Fig. 9 and Table 3.

Similar to Fig. 8, Fig. 9 shows reference and tracked speed profiles. Comparing with the results in Fig. 8(b), vehicle travelling distance, speed limit, and economic speed in Fig. 9(a) are different because the economic route is no longer the fastest one. Fig. 9(b) shows two speed profiles on route R_{S2} for OD2. The notations used in Table 3 are the same as these in Table 1. In Table 3, subscripts 1 and 2 represent OD1 and OD2, respectively. ‘Fast1’ and ‘Fast2’ groups show the simulation results for the fastest route associated with unoptimized speed. ‘Eco E1’ and ‘Eco E2’ groups show the results that the route is optimized based on the current traffic speed (no speed optimization). ‘Eco E1-I/II’ and ‘Eco E2-I/II’ groups show the results that the route and speed are optimized simultaneously by the proposed VMMP method. From Tables 1 and 3, it can be seen that the proposed VMMP method is able to reduce fuel consumption over the vehicle route planning methods with only route or speed optimization. Comparing with the fastest route without optimization, the fuel consumption using the proposed VMMP method can be reduced by up to 15%.

### Table 1

<table>
<thead>
<tr>
<th>Group</th>
<th>Route</th>
<th>Speed</th>
<th>( T_O ) (s)</th>
<th>( T_S ) (s)</th>
<th>Fuel (L)</th>
<th>( \Delta F )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>RS1</td>
<td>V_{S1}</td>
<td>792.7</td>
<td>817.1</td>
<td>1.2435</td>
<td>0</td>
</tr>
<tr>
<td>Eco S-I</td>
<td>RS1</td>
<td>V_{S1}</td>
<td>990.9</td>
<td>986.2</td>
<td>1.1396</td>
<td>−8.60%</td>
</tr>
<tr>
<td>Eco S-II</td>
<td>RS1</td>
<td>V_{S1}</td>
<td>1189.1</td>
<td>1185.0</td>
<td>1.1074</td>
<td>−10.94%</td>
</tr>
<tr>
<td>Fast</td>
<td>RS1</td>
<td>V_{S1}</td>
<td>713.2</td>
<td>735.6</td>
<td>1.3237</td>
<td>0</td>
</tr>
<tr>
<td>Eco F-I</td>
<td>RS1</td>
<td>V_{S1}</td>
<td>891.5</td>
<td>879.5</td>
<td>1.2037</td>
<td>−9.07%</td>
</tr>
<tr>
<td>Eco F-II</td>
<td>RS1</td>
<td>V_{S1}</td>
<td>1069.8</td>
<td>1011.0</td>
<td>1.1900</td>
<td>−10.10%</td>
</tr>
</tbody>
</table>

### Table 2

<table>
<thead>
<tr>
<th>Group</th>
<th>( T_O ) (s)</th>
<th>( T_S ) (s)</th>
<th>( \Delta T )</th>
<th>( F_O ) (L)</th>
<th>( F_S ) (L)</th>
<th>( \Delta F )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eco S-I</td>
<td>989.3</td>
<td>986.2</td>
<td>−0.30%</td>
<td>1.1366</td>
<td>1.1396</td>
<td>0.27%</td>
</tr>
<tr>
<td>Eco S-II</td>
<td>1186.8</td>
<td>1185.0</td>
<td>−0.15%</td>
<td>1.1070</td>
<td>1.1074</td>
<td>0.04%</td>
</tr>
<tr>
<td>Eco F-I</td>
<td>881.2</td>
<td>879.5</td>
<td>−0.20%</td>
<td>1.2052</td>
<td>1.2037</td>
<td>−0.12%</td>
</tr>
<tr>
<td>Eco F-II</td>
<td>1012.7</td>
<td>1011.0</td>
<td>−0.18%</td>
<td>1.1858</td>
<td>1.1900</td>
<td>0.36%</td>
</tr>
</tbody>
</table>

**Fig. 8.** Speed profiles on fixed routes.
5.2. Simulation study with added traffic light

Traffic light is added using the default set of SUMO in this simulation study. The penalty model of traffic light is added to the co-optimization method (see Fig. 2). The OD pair and trip time limit are the same as these used in the speed-oriented simulations in Section 2.2. In addition, due to the traffic light waiting time, the expected trip time is increased to 1.75 times of the route’s minimum trip time. The simulation results are shown in Fig. 10 and Table 4.

The route notations in Table 4 are corresponding to these in Figs. 7 and 10, and other notations are the same as these in Table 1. Comparing with the simulation results in Table 3 for the ideal traffic environment, the fuel economic routes and their fuel consumptions are different under the actual traffic environment with traffic light, even with the same OD pair and expected trip time. In the ideal traffic simulation study, the fuel economic routes are R_{S1} for 1.25T_{E} (see ‘Eco E-I’ group in Table 3) and 1.5T_{E} (see ‘Eco E-II’ group in Table 3); and in the actual traffic simulation study, the fuel economic routes are R_{S1} for 1.25T_{E} (see ‘Eco E-I’ group in Table 4) and 1.5T_{E} (see ‘Eco E-II’ group in Table 4), respectively. In addition, with the same expected trip time, the proposed method in actual traffic environment reduces fuel consumption is less than that in ideal traffic environment, partially due to the fact that the optimized trip time is shorter than the given one. For example, assuming that route R_{i} has 8 traffic lights, the averaged waiting time is 139.7 s calculated by (21) and (22). Then the actual simulated trip time for speed optimization is 930.1 s in ‘Eco E-II’ group based on (20), not the given expected trip time 1069.8 s. This indicates that longer expected trip time is required for the same fuel economy in actual traffic environment; see results in ‘Eco E-III’ group. Note that the simulated trip time is also smaller than the expected one and the fuel consumption is decreased by more than 10% comparing with the ‘Fast’ group in Table 4. It indicates that the penalty model of

![Economic speed profiles for OD1](image1.png)

(a) Economic speed profiles for OD1

![Economic speed profiles for OD2](image2.png)

(b) Economic speed profiles for OD2

**Fig. 9. Economic speed profiles for OD1 and OD2.**

**Table 3**

<table>
<thead>
<tr>
<th>Group</th>
<th>Route</th>
<th>Speed</th>
<th>T_{E} (s)</th>
<th>T_{S} (s)</th>
<th>Fuel (L)</th>
<th>ΔF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fast1</td>
<td>R_{F1}</td>
<td>V_{F1}</td>
<td>713.2</td>
<td>735.6</td>
<td>1.3237</td>
<td>0</td>
</tr>
<tr>
<td>Eco E1</td>
<td>R_{S1}</td>
<td>V_{IE}I</td>
<td>891.5</td>
<td>888.7</td>
<td>1.1518</td>
<td>−12.98%</td>
</tr>
<tr>
<td>Eco E1-I</td>
<td>R_{S1}</td>
<td>V_{IE}I</td>
<td>1069.8</td>
<td>1064.0</td>
<td>1.1174</td>
<td>−15.99%</td>
</tr>
<tr>
<td>Fast2</td>
<td>R_{F2}</td>
<td>–</td>
<td>706.2</td>
<td>712.1</td>
<td>1.2497</td>
<td>0</td>
</tr>
<tr>
<td>Eco E2</td>
<td>R_{S2}</td>
<td>–</td>
<td>868.0</td>
<td>1.0960</td>
<td>1.0690</td>
<td>−12.30%</td>
</tr>
<tr>
<td>Eco E2-I</td>
<td>R_{S2}</td>
<td>V_{IE}II</td>
<td>882.8</td>
<td>881.6</td>
<td>1.0733</td>
<td>−14.12%</td>
</tr>
<tr>
<td>Eco E2-II</td>
<td>R_{S2}</td>
<td>V_{IE}II</td>
<td>1059.4</td>
<td>1043.0</td>
<td>1.0265</td>
<td>−17.86%</td>
</tr>
</tbody>
</table>

**Fig. 10. Route trajectories with traffic light.**
traffic light is feasible for the VMMP problem.

5.3. Simulation study under traffic jam

Another uncertain factor for actual driving is traffic jam or congestion. Under this situation, the real-time route and speed optimization is necessary and beneficial. As shown in Fig. 11, a vehicle travels on the route $R_I$ from O to D. And its trip time and fuel consumption are provided as ‘No jam’ group in Table 5. In this simulation study, the traffic jam (marked in Fig. 11) is assumed to occur when the vehicle is driving on route $R_I$. In case I, the traffic jam is assumed to occur when the vehicle is driving at position $P_1$; in case II, the traffic jam occurs when the vehicle is located at $P_2$. The simulation results are shown in Table 5.

The route notations used in Table 5 are corresponding to these in Fig. 11 and other notations are the same as these in Table 1. It can be seen that the routes and fuel consumption are different for cases I and II. For case I, the vehicle has multiple routes to be selected when the traffic jam occurs, and it could change to a new route ($R_{II}$) based on the proposed VMMP method. The reference speed is also updated in real-time by the proposed method; see Figs. 2 and 3. For case II, the vehicle is driving on highway when the traffic jam occurs and the current route ($R_I$) is the only choice. In this case, the proposed VMMP method is able to reduce the effect of traffic jam by optimizing vehicle reference speed based on traffic flow data in real-time; see Fig. 3. The simulation results indicate that the real-time optimization is able to reduce the effect of traffic jam.

Note that comparing with the ‘No jam’ case, the vehicle in cases I and II consumes more fuel, but the fuel consumption for case I is less than that for case II. It can be seen that if the traffic jam could be predicted before the vehicle arrives at $P_2$, the proposed VMMP method would further improve the fuel economy. That will be the part of future work related to the VMMP problem.

5.4. Simulation study for the effect of different vehicles

Different from the fastest/shortest routing problem, the cost function (fuel consumption) for the VMMP problem is affected by vehicle powertrain characteristics (Zhou et al., 2016). As a result, different vehicle platforms could also have different fuel economic routes and speed profiles. In this simulation study, two different vehicles are used to show the difference in optimization results for the proposed co-optimization method. Two powertrain models are developed in the same way with their architecture shown in Fig. 5 and vehicle parameters shown in Table 6.

The origin-destination pair is set to be the same for both vehicles; see Fig. 12. And the expected trip time is set to be 1.25 and 1.5 times of the fastest route one. The simulation results are shown in Fig. 12 and Table 7.

The route notations used in Table 7 are specified in Fig. 12 and other notations are the same as these in Table 2. The simulation results show that vehicles 1 and 2 have the same fastest route ($R_F$) but different fuel economic routes. The fuel economic route for vehicle 1 is represented by $R_I$ and vehicle 2 by $R_{II}$. Their fuel consumptions are also different but both decrease by up to 15%. It confirms that different vehicles could have different fuel economic routes and speed profiles. Note that the economic routes for vehicles 1 and 2 are neither the fastest route ($R_F$) nor the shortest route ($R_S$). In addition, from Table 3, it can be seen that the economic routes for OD$_1$ maybe the shortest one or may not, and however, these for OD$_2$ are always the shortest route. It can be concluded that the fuel economic route has nothing to do with neither the fastest nor shortest route.

### Table 4

<table>
<thead>
<tr>
<th>Group</th>
<th>Route</th>
<th>$T_E$ (s)</th>
<th>$T_S$ (s)</th>
<th>Fuel (L)</th>
<th>$\Delta F$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fast</td>
<td>$R_{F1}$</td>
<td>713.2</td>
<td>801.9</td>
<td>1.3398</td>
<td>0</td>
</tr>
<tr>
<td>Eco E-I</td>
<td>$R_{II}$</td>
<td>891.5</td>
<td>885.2</td>
<td>1.1979</td>
<td>−10.59%</td>
</tr>
<tr>
<td>Eco E-II</td>
<td>$R_{II}$</td>
<td>1069.8</td>
<td>1039.3</td>
<td>1.1552</td>
<td>−13.78%</td>
</tr>
<tr>
<td>Eco E-III</td>
<td>$R_I$</td>
<td>1248.1</td>
<td>1220.5</td>
<td>1.1429</td>
<td>−14.70%</td>
</tr>
</tbody>
</table>

Fig. 11. Route trajectories under traffic jam.
The above four simulation studies have validated fuel economy improvement and real-time application capability of the proposed VMMP method. The simulation results under the ideal traffic environment show that vehicle fuel consumption using the proposed VMMP method is improved by up to 15% comparing with that over the fastest route without optimization. The simulation results with traffic light and jam show that the proposed VMMP method using the penalty model and adaptive real-time optimization strategy is suitable for real-time implementation. The simulation results based on two vehicle platforms show that different vehicles could have different fuel economic routes and speed profiles.

### 6. Conclusion

A novel vehicle macroscopic motion planning (VMMP) problem, an extension of vehicle route planning problem, has been proposed and studied in this paper. A genetic algorithm based co-optimization method is used to solve the proposed VMMP problem;
and an adaptive real-time optimization strategy is presented to make the real-time optimization possible for real-time applications. The co-simulation results indicate that the proposed VMMP method is able to improve fuel economy by up to 15% over the fastest route; and the penalty model of traffic light makes it feasible for optimization under actual driving conditions. The real-time optimization strategy is able to reduce the effect of the traffic jam by updating route and speed profile in real-time; and different vehicle platforms could lead to different fuel economic routes and reference speed profiles. The significant improvement of vehicle fuel economy (over 15%) has the potential to reduce transportation emissions and cost. The proposed VMMP co-optimization method is able to provide both fuel economic route and reference speed profile for human-driven, connected and autonomous vehicles to improve fuel economy and reduce transportation cost. However, the proposed VMMP method cannot deal with multiple origin-destination pairs at the same time, which is the future work. In addition, the traffic prediction-based hybrid vehicle VMMP optimization problem will also be considered in the future.

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