Abstract—Traditionally, vehicle route planning problem focuses on route selection based on traffic data. This paper proposes a novel extended vehicle route planning problem, called vehicle macroscopic motion planning (VMMP), to optimize vehicle route and speed simultaneously for improved fuel economy within an expected trip time. The required traffic data and vehicle dynamic parameters can be collected through vehicle connectivity which is developed rapidly in recent years. A genetic algorithm based co-optimization method is used to solve the proposed VMMP problem. A co-simulation model, combining a traffic model based on SUMO (Simulation of Urban MOBility) and a Simulink powertrain model, is developed and used for validating the proposed VMMP problem. The simulation results show that the proposed VMMP method is able to significantly improve vehicle fuel economy. Comparing with the fastest route, the fuel economy using the proposed VMMP method is improved by up to 15%. Additionally, a simulation study is designed for different vehicle platforms and the results show that different vehicles could have different economic routes and speed profiles.

1. INTRODUCTION

Vehicle route planning problem is very important in logistics and transportation. In recent years, due to the rapid development of autonomous and connected vehicles, more attention has been paid to it. In addition, the 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 simultaneous optimization of vehicle route and speed based on the vehicle connectivity [1].

The shortest and fastest route navigations are classic vehicle route planning problems and have been widely used in our daily life through navigation tools based on a given origin-destination (OD) pair and online traffic data. A weighted directed graph made up of edge, nodes, and weights is widely used for these route planning problem modeling, and then the fastest/shortest routes can be optimized by some common used methods, such as Dijkstra’s algorithm, Bellman-Ford algorithm, A* search algorithm, and Floyd-Warshall algorithm [2], [3]. Note that the fastest (or shortest) route is the same for different vehicles for a given OD pair with the same departure time. However, the fastest (or shortest) route does not always minimize the fuel consumption [4]. As a result, the optimal fuel economic route cannot be solved by above methods due to the following reasons. First, the route fuel consumption is not only related to traffic data but also affected by factors such as vehicle speed, powertrain characteristics, road grades, driver behaviors, etc. [5]; second, the edge weights (fuel consumption) in directed graph are inter-dependent and affected by neighboring edges, and the route cost is not equal to the sum of edge weights whose nodes compose the route [1], [2]; third, the fuel consumption of an individual edge could be negative due to brake regeneration for a HEV under down hill operations [6], and it worth to note that most of the optimization algorithms mentioned above can only deal with positive edge weights. In fact, vehicle characteristics play an important role in route planning, even for the fastest route. For example, a small passenger car and heavy-duty commercial vehicle could have different fastest routes due to the difference in vehicle acceleration/deceleration performance and speed limit. The existing on-board powertrain controllers and navigation tools can not optimize the route using both traffic data and vehicle characteristics. Fortunately, the developing vehicle connectivity makes it possible in near future to optimize the economic route using both traffic data and vehicle characteristics [7].

Fuel economy related vehicle route planning research got started in the past decades, such as eco-routing navigation [8], green vehicle routing problem (VRP) [1], [9], [10], [11], and pollution VRP [12], [13], [14]. In these literatures, authors try to minimize vehicle fuel consumption and/or emissions through route planning. First, a cost function is established to evaluate fuel consumption or emissions using some fuel estimation models, such as instantaneous fuel consumption model, mean-value phenomenological model, engine-based model, vehicle-based model, comprehensive modal emission model (CMEM), and invariant models [5], [10]. Second, a mathematical model based on the directed graph or a mixed integer linear program (MILP) [9] is formulated for the route planning problem. Third, a fuel economic route is solved using different methods, such as heuristic algorithm [9], [12], robust optimization [14], genetic algorithm (GA) [11], particle swarm optimization approach [15], etc. Their optimized results show that route optimization has the potential to reduce fuel consumption and emissions with fixed traffic (vehicle) speed. E. Demir, et al. [12], A. Franceschetti, et al. [16], and M. Barth, et al. [17] studied the speed optimization problem with a trip time limit and showed that the speed optimization is able

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to decrease fuel consumption on a fixed route with a given trip time limit. 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), a global co-optimization problem, is proposed to find economic vehicle route and speed profile simultaneously that minimize the cost function (e.g., fuel consumption) from origin to destination with an expected trip time over a traffic network. The main contribution of this paper is three-fold. 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 the improved fuel economy. Second, a GA based co-optimization method is proposed to solve the 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 the eco-driving [18] 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 automated vehicles directly.

This paper is organized as follows. The mathematical model of the proposed VMMP problem is formulated in Section II. In Section III, a GA based co-optimization method is proposed to obtain the optimal solution for the VMMP problem. Section IV is devoted to the development of co-simulation models and simulation studies. Section V adds some conclusions.

II. MATHEMATICAL MODEL OF THE VMMP PROBLEM

A. Powertrain-based fuel consumption model

For a given OD pair with an expected trip time, the goal of the proposed VMMP problem is to improve fuel economy by optimizing vehicle route and speed simultaneously. 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 [5].

For a vehicle equipped with an internal combustion engine (ICE), the fuel consumption ($FC$) can be expressed as

$$FC = \int_{0}^{T} \gamma g(t)T_{e}(t)n_{e}(t)dt$$

where $g(t)$ is the rate of fuel consumption obtained from the engine map based on current engine torque ($T_{e}$) and speed ($n_{e}$); $\gamma = 1/95.49 \times 3600$ is a coefficient for unit conversion; and $T$ is trip time. For the VMMP problem, it can be estimated by speed and the associated sensor locations along the road.

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

where $M$ is the number of sensor locations along the route; $v(k)$ is vehicle speed at sensor location $k$; and $\Delta s(k)$ is distance between sensor locations $k$ and $k + 1$.

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

$$m\ddot{v}(k) = \frac{i_{g}(k)i_{0}n_{t}}{R}T_{e}(k) - (mg\beta(k) + 0.5C_{d}A\rho v^{2}(k))$$

$$n_{e}(k) = \frac{30i_{g}(k)i_{0}}{\pi R}v(k)$$

$$i_{g}(k + 1) = g\left(ge(k), v(k), T_{e}(k)\right)$$

where $m$ is vehicle mass including the equivalent rotating mass; $\dot{v}$ is vehicle acceleration calculated by (6) for known speed profiles; $\beta$ is road coefficient combining the road grade ($\theta$) and coefficient ($\zeta$) as shown in (7); $C_{d}$ is drag coefficient; $\rho$ is air density; $A$ is frontal area; $R$ is wheel radius; $\eta_{t}$ is driveline efficient; $i_{g}$ is transmission gear ratio and the gear number $ge$ is determined by the gear-shifting schedule; and $i_{0}$ is final ratio.

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

$$\beta(k) = \zeta(k)\cos\theta(k) + \sin\theta(k)$$

Based upon equations (2), (3), (4), (5), and (6), the fuel consumption model can be simplified as a function of vehicle speed ($v$), road coefficient ($\beta$), and route length ($s$).

$$FC = \sum_{k=1}^{M} f(\beta(k), v(k)) \frac{1}{v(k)} \Delta s(k)$$

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 [17]. And then, the vehicle route and speed along the route are remaining unknowns for fuel consumption calculation and they are the optimization variables of the proposed VMMP problem.

B. VMMP problem formulation

Like other vehicle route planning problems, the traffic network can be simplified into nodes and edges. The nodes represent road intersections or junctions and the edges are road segments connecting two neighboring nodes. For a given OD pair, let $N$ be the number of feasible edges and define a binary matrix $\Phi = \{\phi_{ij}\}_{N \times N}$ 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 $\phi_{ij}$ is equal to 1 if a vehicle could drive from edge $i$ to $j$ directly, and otherwise, it is equal to 0. 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 lights’ positions and timing, etc. These data can be collected based on navigation tools and vehicle connectivity, and they can also be classified and stored by the nodes and edges. For
where $M_n$ is the number of sensor locations on edge $n$.

In addition, let $S_r$, $V_r^C$, $V_r^U$, and $V_r^L$ represent vectors of sensor positions, current traffic speed, upper and low speed boundaries on route $r$, respectively. Note that $S_r$, $V_r^C$, $V_r^U$, and $V_r^L$ have same orders and match with sensor locations along route $r$.

The VMMP problem is a multi-variable global optimization problem to find the optimal route ($r^*$) and speed vectors ($V^*$) that minimize the fuel cost function ($J$) for a given OD pair with an expected trip time. Note that the optimized route and speed of the VMMP problem are corresponding to the given expected trip time.

$$J = \min_{r \in \mathbb{R}} \left( \min_{v \in V_r} \sum_{k=1}^{M_r} f(\beta(k), v(k)) \frac{1}{v(k)} \Delta s(k) \right)$$

where $\mathbb{R}$ is the set of feasible routes for the given OD pair; $V_r$ is the set of speed profiles corresponding to route $r$.

A feasible route ($r$) is an ordered sequence of some edges from $1$ (origin) to $N$ (destination). It can be generated in the following method: choosing the target edges ($\Omega$) with $\sum_{i=1}^{N} \phi_{ik} + \sum_{j=1}^{N} \phi_{kj} = 2, \forall k \in \Omega, k \neq 1, N$, and $i, j \in \Omega$ for route $r$ using constraints (12)-(14), and sorting these selected target edges from $1$ to $N$ using their corresponding connection parameters. For example, suppose two selected edges are $6$ and $8$ with their connection parameters $\phi_{86} = 1$ and $\phi_{68} = 0$, then the route $r$ will be $[1...8 6...N]$.

$$\sum_{j=1}^{N} \phi_{1j} = 1, \sum_{i=1}^{N} \phi_{ik} \leq 1, \forall k \in \Omega, j \in \Omega$$

$$\sum_{i=1}^{N} \phi_{ij} = 1, \sum_{j=1}^{N} \phi_{ijN} = 1, i, j \in \Omega$$

$$\sum_{i=1}^{N} \phi_{ik} + \sum_{j=1}^{N} \phi_{kj} = \begin{cases} 0, \sum_{i=1}^{N} \phi_{ik} = 0 \text{ or } \sum_{j=1}^{N} \phi_{kj} = 0 \\ 2, \sum_{i=1}^{N} \phi_{ik} = 1 \text{ or } \sum_{j=1}^{N} \phi_{kj} = 1 \end{cases}, \forall k \in \Omega, k \neq 1, N, \text{ and } i, j \in \Omega$$

Constraints (12) make sure that the feasible edges for the given OD pair are only travelled at most once; constraints (13) provide the initial and terminal conditions; constraints (14) show that if one edge is selected, there exist both entering and departure edges to make sure that the edges connect with each other. As a result, a one-way continuous route from initial edge to terminal one is formed.

The speed profile ($V_r$) is an array of vehicle speed at each sensor location along route $r$. At each sensor location, the vehicle speed is subject to powertrain dynamics (3)-(6) and associated traffic constraints.

$$V_r^C \leq V_r \leq \min \left( V_r^C, V_r^U \right)$$

where $T_E$ is the expected trip time provided by a driver.

### III. GA BASED CO-OPTIMIZATION METHOD

After the mathematical model of VMMP is obtained, the next step is to solve it for the optimal route and speed profile. For global optimization algorithms, genetic algorithm is commonly used to generate high-quality solutions for optimization and search problems [11]. GA is an iterative procedure relying on bio-inspired operators such as selection, mutation, and crossover.

The vehicle 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. So a GA based method is proposed to co-optimize the vehicle route and speed profile simultaneously; see Fig. 1.

Note that $k_v$ and $k_r$ are iteration indices of speed and route, respectively; and (17) is the terminal criterion

$$r^*(k_r) = r^*(k_r - 1) \cup \left| J_r^*(k_r - 1) - J_r^*(k_r - 1) \right| < \sigma$$

Fig. 1 is self-explanatory and it can be seen that two 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 the speed optimization are provided by selected route individuals (see steps S4 and S5 in Fig. 1), and the fuel consumption of
the optimized speed profile is used as input to the route optimization (see S8 in Fig. 1). The route fuel consumption \((J_t)\) is used to determine if the iteration is converged or not. The population initializations (steps S2 and S4) and genetic operational processes (steps S7 and S10) are very important in this algorithm. Detailed descriptions for S2 and S10 are provided below. Note that the proposed method in Fig. 1 cannot guarantee the economic route and speed are optimal solutions. Because genetic algorithm is a heuristic method and the terminal criterion in (17) is not an optimal condition. However, genetic algorithm is global convergence (Günter Rudolph [19]) and the solutions become closer to the optimal ones when the \(\sigma\) decreases.

1) Step S2 (route population initialization \(P_r(1)\)). Usually, the initial population is generated randomly, distributing uniformly over the possible solution set.

   a) Initialize the route population \((l_{r,p})\), group \((l_{r,g})\) and select size \((l_{r,s})\) for tournament selection in step S10, mutation \((l_{r,m})\) and crossover size \((l_{r,c})\) used for generating the next population in step S10, and iteration number up bounds \(l_{r,i}\) and \(l_{r,o}\) for iteration process \((k_r = k_r + 1)\) and genetic operating in step S10, 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 the route generation method given in Subsection II (B) with constraints (12)-(14);

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

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

   e) Repeat steps b), c), and d) until the size of \(P_r(1)\) is increased to \(l_{r,p}\). Then set \(k_r = 1\) and go to next step S3.

2) Step S10 (generate next population). First, the best individuals are selected from the current (parent) population to produce the next generation. Second, the next population is generated using mutation and crossover, where the mutation introduces new characteristics into selected parent individuals by altering one or more gene values and the crossover produces new individual from more than one parent individuals by displacing some gene values of an individual from others. The detailed mutation and crossover processes are provided below.

   a) Initialize the random route size \((l_{r,r})\) and offspring number of each parent individuals according to \(l_{r,m}\) and \(l_{r,o}\). Note that the next population \(P_r(k_r + 1)\) is made up of random \((l_{r,r})\), selected \(P_r^r(k_r)\) (\(l_{r,s}\)) and their offspring routes \((l_{r,p} - l_{r,r} - l_{r,s})\);

   b) Select two random edges \((n_1\) and \(n_2\)) in the parent route from selected ones \(P_r^r(k_r)\);

   c) Mutation: create a new partial route from \(n_1\) to \(n_2\) using the route generation method given in Subsection II (B) with constraints (12)-(14), and replace the partial route of parent individual to generate a new one;

   d) Crossover: find the same edges \(\Psi\) between two parent routes \((r_1\) and \(r_2\)). Then select a random edge \((n)\) from \(\Psi\) and generate a new route by combining the partial route for edge 1 to \(n\) in \(r_1\) and partial route for edge \(n\) to \(N\) in \(r_2\);

   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 S2), give it up and repeat steps b), c)/d), and e); otherwise, store it into \(P_r(k_r + 1)\);

   f) Repeat steps b), c), d), and e) until the size of \(P_r(k_r + 1)\) is increased to \((l_{r,p} - l_{r,r} - l_{r,s})\) and generate \(l_{r,r}\) random routes using the above method (S2).

The premature convergence is a 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 [20]. In this paper, the random offspring generation and tournament selection (steps S7 and S10) are used to avoid it. In addition, large population size can be used to avoid the premature convergence with the penalty of computational load. Therefore, a primary selection based on evaluation I (see step S3 in Fig. 1) is utilized to reduce the computational load. The approximate cost function \((J_t)\) 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 [13]. Three speed profiles are used for \(J_t\) calculation: upper speed boundary, low speed with \(T_E\), and economic speed according to the ideal MPG model. The cost function \(J_t\) is the minimum of three costs.

IV. SIMULATION VALIDATION

A. Co-simulation model

A co-simulation model combining traffic and powertrain models is developed to validate the proposed VMMP method; see Fig. 2. The VMMP model and optimization is compiled in m-code; the traffic model is built in SUMO; and the forward powertrain model is established in Matlab/Simulink. The connection between SUMO and Matlab/Simulink models is realized by the TraCI4Matlab, an API (application programming interface) developed in Matlab. It allows controlling SUMO objects such as vehicles, traffic lights, junctions, etc. The simulation steps of the traffic and powertrain models should be the same and are set to be 0.01 s in this study.

![Fig. 2. Simulation architecture using SUMO and Matlab/Simulink](image-url)

The traffic model is able to provide both macroscopic (e.g., traffic speed, etc.) and microscopic traffic data (e.g., vehicle speed and position, traffic light information, etc.). A real traffic network between Novi and Southfield, MI
is downloaded from OpenStreetMap, firstly, and then, converted to SUMO network model with modifications by JOSM (Java OpenStreetMap) editor. After that, traffic flow and other model parameters are generated and set using SUMO applications. The detailed modeling process can be found in [21].

Two powertrain models are used in this research, backward and forward powertrain models. The former is used for cost calculation; see Section II, and the latter is used to track the fuel economic speed in simulations. The main difference between these two models is driver model. The backward model calculates the fuel consumption based upon the given vehicle speed so that the driver model is not required. But for real-time simulations, the driver model is required to follow the reference speed. The forward powertrain model is developed in Simulink, 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.

B. Speed-oriented simulation on fixed routes

Similar to other related research, 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: a) traffic lights are assumed to be green so that the vehicle can travel through an intersection without braking and waiting; b) there is no traffic jam and surrounding vehicles keep safety distances with the studied vehicle; and c) lane changing does not increase the route length and vehicle fuel consumption.

Different from 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 given OD pair is shown as O₁D in Fig. 3. The test routes are set to be the shortest (R₁₂₁) and fastest routes (R₈₁), respectively. The expected trip time (Tₑ) are set to be 1.25 and 1.5 times of the route’s minimum trip time (Tₘᵢₙ), respectively.

![Fig. 3. Route trajectories for the given OD pairs](image)

The notations of routes in Table I are corresponding to these in Fig. 3. Tₛ is the simulated time and ΔF is the fuel consumption difference between the unoptimized (‘Fast’ and ‘Short’ groups in Table I) and optimized speed. The Tₑ 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, Tₛ are slightly larger than Tₑ for these two groups. From Table I, it can be seen that as expected speed optimization is able to decrease the fuel consumption with about 10% saving. The simulated time duration of ‘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 D within the trip time limit. This indicates that the proposed speed optimization is able to improve the fuel economy within the expected trip time.

C. Simulation study on both vehicle route and speed

Next, the simulation study for the proposed GA based co-optimization of vehicle route and speed are carried out. In this simulation study, only origin-destination and corresponding trip time limits are given. In order to have a fair comparison, the trip time limits are set to be the same as these used in above speed-oriented simulations. The simulation results are provided in Table II.

![Table I. Fuel consumption and trip time comparison on fixed routes](image)

<table>
<thead>
<tr>
<th>Group</th>
<th>Route</th>
<th>Tₑ(s)</th>
<th>Tₛ(s)</th>
<th>Fuel(L)</th>
<th>ΔF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short</td>
<td>R₁₂₁</td>
<td>792.7</td>
<td>817.1</td>
<td>1.2435</td>
<td>0</td>
</tr>
<tr>
<td>S-I</td>
<td>R₁₂₁</td>
<td>990.9</td>
<td>986.2</td>
<td>1.1396</td>
<td>-8.60%</td>
</tr>
<tr>
<td>S-II</td>
<td>R₁₂₁</td>
<td>1189.1</td>
<td>1185.0</td>
<td>1.1074</td>
<td>-10.94%</td>
</tr>
<tr>
<td>Fast</td>
<td>R₁₂₁</td>
<td>713.2</td>
<td>735.6</td>
<td>1.1396</td>
<td>0</td>
</tr>
<tr>
<td>F-I</td>
<td>R₁₂₁</td>
<td>891.5</td>
<td>879.3</td>
<td>1.2037</td>
<td>-9.07%</td>
</tr>
<tr>
<td>F-II</td>
<td>R₁₂₁</td>
<td>1069.8</td>
<td>1011.0</td>
<td>1.1900</td>
<td>-10.10%</td>
</tr>
</tbody>
</table>

The notations of routes in Table II are corresponding to these in Fig. 3 and other notations are the same as these in Table I. In Table II, group ‘E-I’ shows the results that the route is optimized based on the current traffic speed (no speed optimization). ‘E-II’ and ‘E-III’ groups show the results that the route and speed are optimized simultaneously by the proposed VMMP method. From Tables I and II, it can be seen that the proposed VMMP method is able to reduce fuel consumption over the other methods with only route or speed optimization.

D. 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 the vehicle powertrain characteristics [5]. As a result, different vehicle platforms could have different fuel economic routes and speed profiles. In this simulation study, two different vehicles are used to show the different optimization results for the proposed co-optimization method.
The masses of vehicles 1 and 2 are 1600 kg and 2400 kg, respectively. And the maximum engine power are 100 kW and 246 kW, respectively.

The origin-destination pair is set to be the same for both vehicles; see O₂D in Fig. 3. 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 Table III.

### TABLE III

<table>
<thead>
<tr>
<th>Group</th>
<th>Vehicle</th>
<th>Route</th>
<th>$T_E$(s)</th>
<th>$T_G$(s)</th>
<th>Fuel(L)</th>
<th>$\Delta F$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fast</td>
<td>Veh₁</td>
<td>R₁F₂</td>
<td>630.4</td>
<td>641.3</td>
<td>0.9619</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Veh₁</td>
<td>R₁E₁</td>
<td>788.0</td>
<td>786.9</td>
<td>0.8404</td>
<td>12.63%</td>
</tr>
<tr>
<td></td>
<td>Veh₁</td>
<td>R₁E₁I</td>
<td>945.6</td>
<td>935.5</td>
<td>0.8156</td>
<td>15.21%</td>
</tr>
<tr>
<td>Fast</td>
<td>Veh₂</td>
<td>R₂F₂</td>
<td>630.4</td>
<td>646.7</td>
<td>1.7138</td>
<td>18.29%</td>
</tr>
<tr>
<td></td>
<td>Veh₂</td>
<td>R₂E₁II</td>
<td>788.0</td>
<td>783.2</td>
<td>1.4178</td>
<td>-17.46%</td>
</tr>
<tr>
<td></td>
<td>Veh₂</td>
<td>R₂E₁I</td>
<td>945.6</td>
<td>940.9</td>
<td>1.4036</td>
<td>-18.29%</td>
</tr>
</tbody>
</table>

The route notations in Table III are specified in Fig. 3 and other notations are the same as those in Table I. The simulation results show that vehicles 1 and 2 have the same fastest route (R₁F₂) but different fuel economic routes. The fuel economic route for vehicle 1 is represented by R₁E₁ and R₁E₁I for vehicle 2. 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 fuel economic routes for vehicles 1 and 2 are neither the fastest route (R₁F₂) nor the shortest route (R₂E₁II). It can be concluded that the fuel economic route has nothing to do with the fastest and shortest routes.

### V. CONCLUSIONS

A novel vehicle macroscopic motion planning (VMMP) problem, an extension of the 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. The co-simulation results indicate that the proposed VMMP method is able to improve the fuel economy for up to 17.86% over the traditional methods with only route or speed optimization. The different vehicle platforms could lead to different fuel economic routes and speed profiles. The proposed VMMP co-optimization method is able to provide both fuel economic route and reference speed profile for driver to improve the fuel economy and it also provides a foundation for autonomous vehicle to optimize the vehicle fuel economy. The future work is focused on traffic lights, traffic prediction, and hybrid vehicle VMMP optimization.

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