

Research Article

A Novel On-Ramp Merging Strategy for Connected and Automated Vehicles Based on Game Theory

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Connected and automated vehicles (CAVs) have attracted much attention of researchers because of its potential to improve both transportation network efficiency and safety through control algorithms and reduce fuel consumption. However, vehicle merging at intersection is one of the main factors that lead to congestion and extra fuel consumption. In this paper, we focused on the scenario of on-ramp merging of CAVs, proposed a centralized approach based on game theory to control the process of on-ramp merging for all agents without any collisions, and optimized the overall fuel consumption and total travel time. For the framework of the game, benefit, loss, and rules are three basic components, and in our model, benefit is the priority of passing the merging point, represented via the merging sequence (MS), loss is the cost of fuel consumption and the total travel time, and the game rules are designed in accordance with traffic density, fairness, and wholeness. Each rule has a different degree of importance, and to get the optimal weight of each rule, we formulate the problem as a double-objective optimization problem and obtain the results by searching the feasible Pareto solutions. As to the assignment of merging sequence, we evaluate each competitor from three aspects by giving scores and multiplying the corresponding weight and the agent with the higher score gets comparatively smaller MS, i.e., the priority of passing the intersection. The simulations and comparisons are conducted to demonstrate the effectiveness of the proposed method. Moreover, the proposed method improved the fuel economy and saved the travel time.

1. Introduction

Congestion has caused many problems such as excessive fuel consumption and increased travel time in the real transportation system. According to a survey, the total cost of congestion in urban areas in the United States was estimated at 160 billion dollars and an extra 3.1 billion gallons of fuel consumed in 2014 [1]. Collaborative control of connected autonomous vehicles (CAVs) in a networked environment enables vehicles to cooperate with each other through information interaction, which can improve the road traffic efficiency and reduce the energy consumption while ensuring safety. To achieve the cooperative control of vehicles, advanced localization [2] and communication technologies

[3, 4] (including V2V (vehicle to vehicle) and V2I (vehicle to infrastructure) communication, etc.), are required to assist the autonomous vehicle making decisions. Control of CAVs can be applied to many issues related to transportation optimization, and one of them is on-ramp merging of vehicles. In fact, on-ramp merging is one of the main causes of traffic congestion and the bottleneck of the traffic efficiency [5] since vehicles attempting to merge may initially slow down even and stop on the on-ramp to await a proper opportunity to merge. CAVs controlled by algorithms with high efficiency are expected to be able to reduce traffic congestion and enhance vehicle safety [6–9]. More key technologies and algorithms for CAVs control have been surveyed in [10].

The essence of the on-ramp merging problem is the competition for the priority of passing the merging area and reflected on the assignment of merging sequence (MS) for CAVs under the control of a centralized controller. We can regard such competition as a game in which every agent (i.e., the connected autonomous vehicle) competes for the prior merging sequence. Contribution of this paper just lies in the game framework we developed. In this paper, we propose a centralized approach based on game theory to control the on-ramp merging of all agents without any collisions and reduce the cumulative fuel consumption and total travel time. As to the game, we regard vehicles on the same road as a group and they will collaborate to compete with another group. Benefit, loss, and rules are three basic components in a game, and in our framework, benefit is the priority of passing the merging point and loss is the cost of fuel consumption and the travel time. Rules are the core for a game since agents in each group take actions based on the game rules to maximize the benefits and minimize the loss, and we proposed three basic rules in accordance with the Traffic Density Principle, FIFO (First In First Out) Principle, and Wholeness Principle, respectively. Importance of three rules varies, and we formulate the problem as a double-objective optimization problem of cumulative fuel consumption and total travel time, searching the feasible Pareto solutions to ascertain the weight of each rule.

Simulations and comparisons are conducted to validate the effectiveness of the proposed framework. Contribution of this paper mainly lies in the (1) construction of the framework for global optimal merging of CAVs based on the game theory and (2) approaches to searching the Pareto solutions and ascertaining the optimal weights of three rules via back search through formulating the problem as a double-objective optimization problem.

The structure of the paper is depicted as follows. In Section 2, we will introduce the related work. Section 3 describes the problem framework. Modeling and solution will be illustrated in Section 4, and simulation results and analysis will be displayed in Section 5. We end the manuscript with conclusions in Section 6.

2. Related Work

Current researches of on-ramp merging mainly focus on the scheduling algorithm of passing vehicles per unit time and control of merging at the expressway to improve the traffic efficiency [11–15]. A series of related control algorithms, control strategies, and scheduling algorithms are proposed under security principles. For example, in 2004, Dresner and Stone [16] proposed an automatic intersection control method based on retention algorithm. Generally, research work of CAVs on-ramp merging can be divided into centralized methods and decentralized methods [17], and both of these two categories have been studied [18–21]. Ntousakis et al. [20] proposed a decentralized automatic merging algorithm, in which each vehicle makes use of the information received from other agents to ascertain the appropriate sequence to merge on the ramp, and experiments show that the algorithm is safely executed and the traffic stability is well

maintained. In comparison to the decentralized methods, centralized approaches have also been widely discussed. Cao et al. [21] have proposed the concept of cooperative merging, in which only the vehicles on the main road get the information of the vehicles on ramp road from the centralized controller and then adjust their speed to optimize the passing efficiency. In [22], both centralized and decentralized methods are adopted and a trajectory planning method is proposed to optimize engine efficiency and passenger comfort by adding jerk (derivative of acceleration) in the objective function. The analytical solution is obtained using the optimal control theory and the linear quadratic regulator method, and the model predictive control scheme is then used to compensate for potential interference in the trajectory.

However, most of the methods discussed focus on the optimization of vehicle trajectories with little or no emphasis on the calculation of the best merge sequence (MS), and few studies have discussed the creation of MS assignment [23]. Besides, game theory is also seldom seen in the literature related to the research about on-ramp merging. In essence, issue of vehicles merging at intersection can be regarded as the competition for a prior MS from the angle of an individual agent, which means that small MS represents the priority of passing the merging point. In [24], Jing et al. proposed a cooperative multi-player game-based optimization framework to coordinate vehicles and achieve minimum values for the global payoff conditions. To simplify the problem, the multiplayer games were decomposed into multiple two-player games and finally formulated as an optimization problem and got an analytic solution.

We also apply game theory to deal with the on-ramp merging issue but the differences between our work and [24] primarily lie on the following: (1) cooperation is allowed among vehicles on the same road, and the competition is between two groups; (2) more aspects, like traffic intensity, fairness, and wholeness principle, are considered when designing the game rules.

3. Problem Framework

The scenario of vehicle merging consists of a main road and a ramp road and both of them are single lane. We assume there exists a centralized controller that can communicate with all vehicles in the control area without any time delay. The control area is divided into *Game Area*, where each agent adopts its optimal strategy according to the game rules, and *Adjusting Area*, where each agent adjusts their states to cooperatively pass the merging point O without any collisions. O is the origin of the coordinates, and the two roads are noted as X_m and X_r , representing the main road and ramp road, respectively, and the length of *Game Area* and *Adjusting Area* is G and M , as shown in Figure 1.

Assume that there are W vehicles passing the merging point during the research time and the centralized controller will assign the passing sequences i ($i = 1, 2, \dots, W$) to each agent at the moment when the first vehicle V_1 reaches the *Adjusting Area*, in accordance with the states of all vehicles at

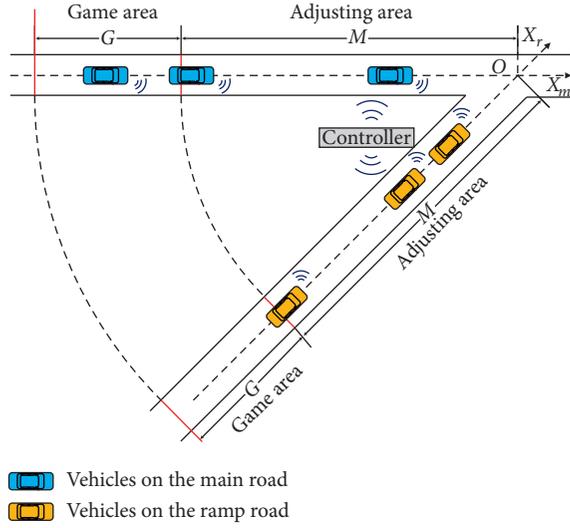


FIGURE 1: General framework of the proposed system.

that moment. Each vehicle V_i is modeled as a point mass and its state is described as

$$\chi_i(t) = [p_i(t), v_i(t), a_i(t)], \quad (1)$$

where $p_i(t)$, $v_i(t)$, $a_i(t)$ represent the position (or coordinate value), velocity, and acceleration of the vehicle V_i at the time t and $t=0$ is the moment when the W th vehicle V_W enters the *Game Area* (we assume that length of the *Game Area* is long enough and the first vehicle V_1 is still in *Game Area* at $t=0$).

4. Modeling and Solution

Game theory is the cornerstone of the proposed model, and in this section, we will illustrate our model in detail and formulate the problem and then give a numeric solution based on searching Pareto solutions.

4.1. Priority of Passing Game. In a game, each player tends to make the best decision for himself/herself based on the obtained information and game rules. In *Game Area*, each agent can obtain the information of other agents from the central controller and try to gain the maximum benefits with minimum cost based on a series of rules and the information obtained. Here, $t=0$ is the time when the game begins, and the game ends at the moment when the first vehicle reaches the *Adjusting Area*. And, in this part, we will illustrate the benefits, cost, and rules in detail.

During the gaming period, vehicles on the same road take the strategy of cooperation since overtaking is not allowed on a single lane road. We regard all vehicles on the main road as a group to compete with another group consisting of all vehicles on the ramp road, and each group tends to strive for the maximum benefits with least possible cost from the holistic perspective. Benefits are the merging sequences (MS, also known as passing sequences) assigned to each vehicle, and small MS represents a senior right to pass the merging point. The cost is originated from state

changing of the vehicles, represented via fuel consumption, and the rules are given empirically and listed as below:

Rule 1: vehicles in the group that contains more vehicles are more prior to pass

Rule 2: vehicles that are closer to the merging point O , i.e., have greater coordinate values, are more prior to pass

Rule 3: vehicles with smaller mean space gap from its preceding agent and its following agent are more prior to pass

These rules can be explained via three principles, i.e., Traffic Density Principle, FIFO Principle, and Wholeness Principle, respectively.

Rule 1 takes the Traffic Density Principle into consideration. If one of the roads has more vehicles, it means the traffic density of this road is higher and gives passing priority to the vehicles on this road which will improve the traffic efficiency (represented by the passing time of all vehicles).

Rule 2 is in accordance with the FIFO Principle, and this rule is related to fairness. Assume there are two roads, i.e., Road A and Road B, converging at an intersection, and the traffic density of Road A is much greater than Road B. The traffic efficiency will be improved if vehicles on Road B stop before the merging area to await the vehicles on another road passing through the merging point. But such a situation is unfair to the vehicles on Road B because they suffer from a jam at the same time.

Rule 3 is related to the Wholeness Principle. Considering the scenario shown in Figure 2, x_j ($j=1,2,\dots,6$) represents the coordinate values of vehicle V_j and $x_1 > x_2 > x_3 > x_4 > x_5 > x_6$. Among these vehicles, $V_2, V_3,$ and V_5 are on the main road and $V_1, V_4,$ and V_6 are on the ramp road, and the spacing gap between V_2 and V_3 is much smaller than that between V_1 and V_4 . Assume V_1 and V_2 will have a collision when merging if none of them change their states, and in this case, adjusting V_1 pays less cost than adjusting V_2 and V_3 . That means V_2 and V_3 share more “wholeness” than V_1 and V_4 and should have the priority to pass the merging point as a whole. Similar analysis can be done to $V_4, V_5,$ and V_6 . In fact, this rule is the extension of *Rule 1* embodied in a specific local area and represented by measuring the mean space gap of a vehicle between its preceding one and its following one (the first vehicle on a road uses the gap between itself and its following one to describe this attribute, while the last vehicle on a road uses the gap between itself and its preceding one to describe this attribute). For example, L_{23} depicts such attribute to V_2 and $(L_{23} + L_{35})/2$ to V_3 .

Based on these three rules aforementioned, each vehicle will adjust their states during gaming period with two motivations, i.e.,

- (a) Gaining a coordinate value as greater as possible (O is the origin of coordinates and the positive direction is the moving direction of vehicles, as shown in Figure 1.)
- (b) Narrowing the space gap between successive vehicles under the safe vehicle space distance constraint

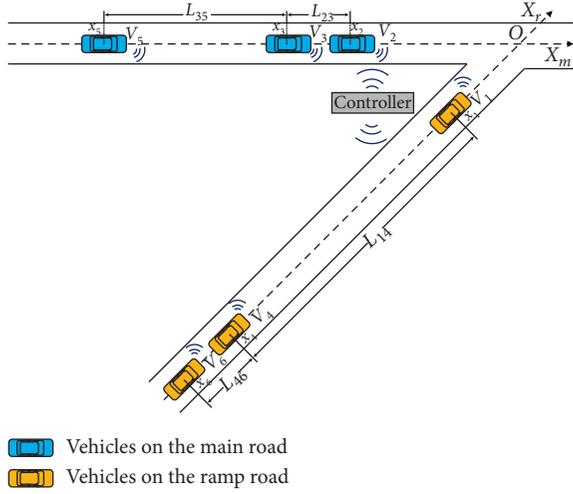


FIGURE 2: Scenario illustrating Rule 3.

We use IDM (intelligent driver model) to depict following vehicles in a group, and the leader vehicle for each group will adopt the strategy of speeding up. Once there is a vehicle reaching the *Adjusting Area*, the game ends and we note this moment as t_f . And, the controller assigns MS to each vehicle according to the states of all vehicles at t_f moment. IDM [25] is formulated as follows:

$$v(t) = v(t-1) + \Delta t \cdot \alpha \left[1 - \left(\frac{v(t-1)}{v_0} \right)^4 - \left(\frac{S_0 + v(t-1) \cdot T_h + ((v(t-1) \cdot \Delta v) / 2 \sqrt{\alpha\beta})}{S} \right) \right], \quad (2)$$

where $v(t)$ is the velocity at moment t , which can be iteratively obtained from $v(t-1)$, Δt is the interval of two successive time frames, v_0 is the velocity that the vehicle expects to achieve, S is the real distance between the vehicle and its preceding one, S_0 is the minimal safety distance between two vehicles, T_h is the time headway, Δv is the velocity difference between two successive vehicles (note: $v_p(t)$ is the velocity of the preceding vehicles at moment t , $\Delta v = v(t-1) - v_p(t-1)$), and α and β are two parameters.

Equation (2) is a linear control law to maintain the stability of a group of vehicles (also called “a platoon”), but this model may generate unstable acceleration, especially at the initialization and state switching moment. We will illustrate such cases in detail in the next part of this section.

As mentioned above, we evaluate each vehicle from 3 aspects, i.e., number of vehicles in its group, distance from the merging point O , and mean space distance of a vehicle between its preceding one and its following one, via scoring at the moment t_f . For each item, the vehicle which performs the best gets 10 scores and the worst one gets 1 scores, and the others linearly get the corresponding scores. For example, to get the score that evaluates the distance from the merging point (assuming the coordinate value for each vehicle V_j is x_j ; ($j = 1, 2, \dots, n$)), we firstly set the vehicle with the maximum coordinate value $\max(x_j)$ as 10 and the

vehicle with the minimum coordinate value $\min(x_j)$ as 1 and then obtain the linear coefficient vector $K_2 = [k_2, b_2]^T$:

$$K_2 = [k_2, b_2]^T = \begin{bmatrix} \max(x_j) & 1 \\ \min(x_j) & 1 \end{bmatrix}^{-1} \cdot \begin{bmatrix} 10 \\ 1 \end{bmatrix}. \quad (3)$$

Each vehicle V_j can be scored as

$$S_2 = [s_2^1, s_2^2, \dots, s_2^n]^T = \begin{bmatrix} x_1 & x_2 & \dots & x_n \\ 1 & 1 & \dots & 1 \end{bmatrix}^T \cdot K_2. \quad (4)$$

Similar technique can be applied to get the score S_3 that evaluates the mean space distance of a vehicle between its preceding one and its following one:

$$K_3 = [k_3, b_3]^T = \begin{bmatrix} \min(d_1) & 1 \\ \max(d_n) & 1 \end{bmatrix}^{-1} \cdot \begin{bmatrix} 10 \\ 1 \end{bmatrix}, \quad (5)$$

$$S_3 = [s_3^1, s_3^2, \dots, s_3^n]^T = \begin{bmatrix} d_1 & d_2 & \dots & d_n \\ 1 & 1 & \dots & 1 \end{bmatrix}^T \cdot K_3,$$

where K_3 is the linear coefficient and d_k ($k = 1, 2, \dots, n$) is the mean space gap of vehicle V_k between its preceding one and its following one.

The scores $S_1 = [s_1^1, s_1^2, \dots, s_1^n]^T$ are used to evaluate the number of vehicles in a group, and the vehicles in the same group will get the same score. Note Num_m as the number of vehicles on the main road and Num_r as the number of vehicles on the ramp road, and then all vehicles on the main road is scored as $Num_m / (Num_m + Num_r)$ and $Num_r / (Num_m + Num_r)$ for all vehicles on the ramp road.

The weight vector $w = [w_1, w_2, w_3]^T$ is assigned to describe the importance of S_1 , S_2 , and S_3 correspondingly. We can get the final score S as

$$S = [S_1 \ S_2 \ S_3] \cdot w. \quad (6)$$

As the method of giving the optimal weight vector w , we use the searching approach that will be illustrated in Section 3. And, the controller assigns the MS according to the final score. The higher score a vehicle gets, the smaller sequence (means it is more prior for the vehicle to pass the merging point O) the vehicle obtained.

However, it may occur that the vehicle in front is assigned a bigger MS than the vehicle behind in a group. In this case, vehicles in the same group should adjust their MS in accordance with their distance to the merging point O (the closer to the merging point, the smaller sequence is obtained) since overtaking is not allowed on a single lane road.

4.2. State Adjusting. Once the game ends at moment t_f , the state adjusting process starts and we assume the length of *Adjusting Area* is long enough for state adjusting. We map all vehicles into one dimension, and all vehicles get a sequence based on their coordinate values, called position sequence (PS). The bigger the coordinate value of a vehicle, the smaller PS it gets. There are 3 possible relationships between MS and PS, i.e., $MS = PS$, $MS > PS$, and $MS < PS$. By comparing the MS and PS, each vehicle will respond differently, as shown below.

4.2.1. $MS = PS$. $MS = PS$ means the merging sequence for a vehicle is the same to the position sequence, and maintaining the current state will consume the least fuel. In this circumstance, the vehicle will simply obey the IDM model, but the reference vehicle may not on the same road. As shown in Figure 3, V_1 and V_3 are on the same road and V_2 is on another road, while the relationship of their coordinate values is $x_1 > x_2 > x_3$ and the MS relationship is $MS_1 < MS_2 < MS_3$. For V_3 , its reference vehicle is V_2 , not V_1 .

As we mentioned in the previous part, IDM may generate acceleration jumping especially at the state switching moment. When we map all vehicles into one dimension, the reference vehicle for an agent may change, which is equivalent to that its “preceding” vehicle’s state abruptly changes and it causes the acceleration jumping. To solve this problem, we constrain acceleration within certain range to avoid the unexpected jumping.

4.2.2. $MS > PS$. $MS > PS$ means the merging sequence for a vehicle is more prior than its real position sequence. Therefore, it should adopt the strategy of accelerating only if the space distance of the vehicle and its preceding one is greater than the minimal safe distance.

4.2.3. $MS < PS$. $MS < PS$ means the vehicle should make concessions to other vehicles. Therefore, it should adopt the strategy of decelerating until it receives the signal which indicates that the PS of the vehicle is already in accordance with its MS from the controller. Then, the vehicle just simply adopts the IDM model illustrated in the part “ $MS = PS$.”

4.3. *Optimization for Fuel Consumption and Travel Time.* In the previous section, we discussed the possible actions that each vehicle can take in different periods (i.e., gaming period and adjusting period). We can conclude that the strategy a vehicle adopts in gaming period is in accordance with the game rules, and the weight vector $w = [w_1, w_2, w_3]^T$ measures the importance of different rules and its value will influence the assigning of the MS to each vehicle. Therefore, we try to find an optimal w to get a reasonable MS so that the fuel consumption and total travel time can be optimized. This is a typical optimization problem of two objectives and can be formulated as

$$\begin{aligned} \min, \quad & J = \mu F + \gamma T = g(w = [w_1 \ w_2 \ w_3]^T), \\ \text{s.t.} \quad & a_i(t) \in [a_{\min}, a_{\max}], v_i(t) \in [0, v_{\max}], \sum_{j=1}^3 w_j = 1, \end{aligned} \quad (7)$$

where F is the total fuel consumption, T is the total travel time, g is the function that denote the relationship between weight vector w and the optimization object, a_{\min} and a_{\max} are the minimum deceleration and maximum acceleration, respectively, v_{\max} is the maximum speed limit, and μ and γ are two parameters that can adjust the object function.

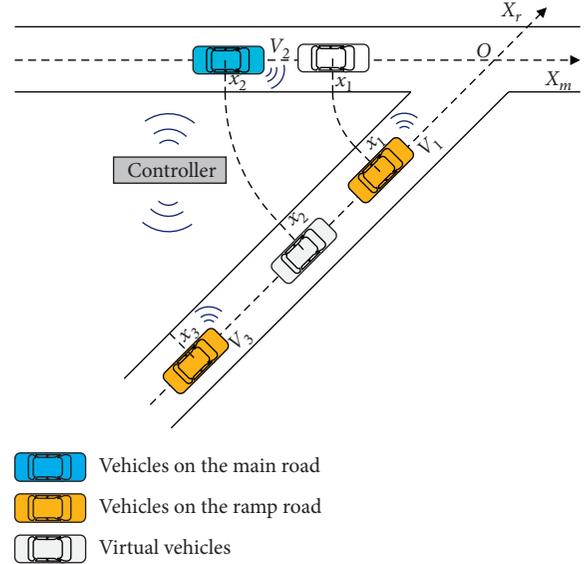


FIGURE 3: Explanation to the reference vehicle.

As to the fuel consumption, we refer to [26, 27] and adopt the estimation as

$$\begin{aligned} f &= f_v + f_a, \\ f_v &= q_0 + q_1 v(t) + q_2 v^2(t) + q_3 v^3(t), \\ f_a &= a(t) \cdot (r_0 + r_1 v(t) + r_2 v^2(t)), \end{aligned} \quad (8)$$

where f is the instantaneous fuel consumption consisting of f_v and f_a , representing instantaneous fuel consumption caused by velocity and acceleration, respectively. If the acceleration value is negative, we use the absolute value instead. Coefficient vectors $q = [q_0, q_1, q_2]$ and $r = [r_0, r_1, r_2]$ are obtained from the experiment [28], and the values are $q = (0.1569, 2.45 \times 10^{-2}, -7.415 \times 10^{-4})$ and $r = (0.07224, 9.681 \times 10^{-2}, 1.075 \times 10^{-3})$. The total fuel consumption is the sum of instantaneous fuel consumption in each moment for all vehicles from $t=0$ (the moment when the last vehicle arrives to the *Game Area*) to the moment when the last vehicle passes the merging point O , noted as t_F .

About the total travel time T , we start timing at $t=0$ and end timing at $t=t_F$, and $T=t_F-0=t_F$.

From Formula (7), we can see that F and T are functions of w , but we do not know the explicit expression of g ; therefore, we cannot solve the optimization problem analytically based on (7). Besides, for a double-objective optimization problem, there usually does not exist such a solution where both objectives are optimized; we should make a trade-off between objectives according to practical requirement. Here, we will find a feasible Pareto solution [29] for this problem. A Pareto solution is the solution where further optimization for an objective is always at the cost of the deterioration of other objectives. For example, as shown in Figure 4, A and B are two objectives we dedicate to minimize and (x_1, y_1) is a Pareto solution, because if we continue decrease the value near x_1 to optimize objective A , the performance of objective B will deteriorate. Situation for (x_3, y_3) is similar to (x_1, y_1) , while (x_2, y_2) is not a Pareto solution since both objectives can be further minimized near this point. There

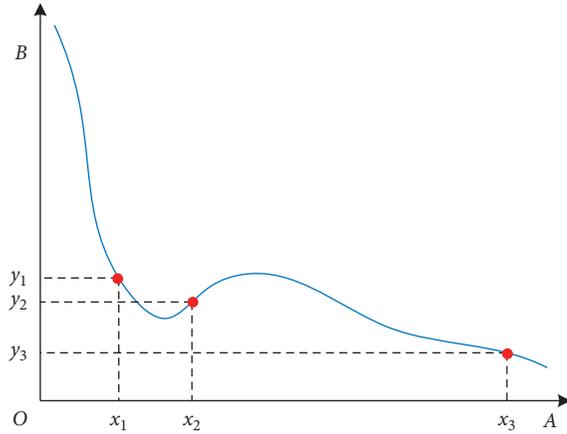


FIGURE 4: Illustration of the Pareto solution.

are many Pareto solutions in a double (or multiple) objective optimization problem, and these solutions consist a solution set (called Pareto front), as shown in Figure 4. There are feasible solutions in such sets and we select the best fit in accordance with the trade-off between different objectives.

4.4. Searching for the Pareto Solution. From previous part, we conclude that possible acceptable solutions can be found in the Pareto front set. In our problem, two optimization objectives are cumulative fuel consumption F and total travel time T , and in this part, we give the steps of searching Pareto solutions for this specific problem:

Step 1: divide w with comparatively large step size and compute the cumulative fuel consumption F and total travel time T .

In this step, we divide each component of w with stride of 0.05, under the constraint that the sum of all components is 1. For each node, compute F and T for N times (N is the repeated computing times for a node, for example, $N=100$) and average the results.

Step 2: subdivide w in the sparse area.

By analyzing the results in Step 1, the distribution of the results in some range may happen to be sparse. We further subdivide w in these sparse range with stride of 0.01, even much smaller, and compute F and T for N times at these subdivided nodes.

Step 3: find the “inflection points” on the F - T curve.

Figure 5 is a F - T curve we get in one of our simulation experiments and we call points C and D “inflection” points where optimizing one of the objectives will lead to large deterioration of another objective. In acceptable range of F and T , we regard these points as the best trade-off of different objectives according to practical requirements and choose one of them as the “best” fit for the problem.

Step 4: back search for the corresponding w .

We choose point $C(T_c, F_c)$ as the best trade-off of our two objectives and search back to find the w that correspond

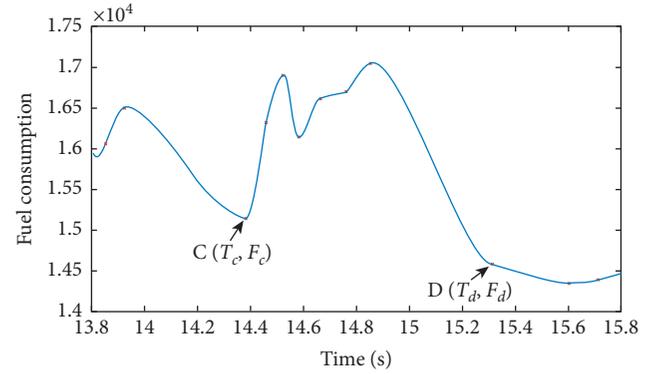


FIGURE 5: F - T curve in one experiment. The red dot is the simulation results, and the blue curve is the shape preserving interpolation based on the red dot.

to (T_c, F_c) . There can be several proper values for w and any one of them can be chosen as the solution.

5. Simulation Results and Analysis

To display the simulation results of the trajectory, velocity, acceleration, and fuel consumption during gaming and adjusting periods, we should firstly ascertain a weight vector $w = [w_1, w_2, w_3]$. Based on the steps of searching Pareto solutions described in the previous section, we select $w = [0.15, 0.45, 0.4]$ as the best fit, and all case studies are under such condition. Besides, we set a “sliding window” parameter W to decide the number of agents per game.

5.1. Case Study 1: “Sliding Window” Parameter $W=5$. This simulation is to verify the effectiveness under the condition that the number of vehicles is comparatively small in one turn of a game, in this case, 5 CAVs driving on the two merging roads. The entry time and the number of vehicles on main road and ramp road are random. The value of the time-headway can be in the range of $[1.2\text{ s}, 2.4\text{ s}]$ in different scenarios [30] and here we choose $T_h = 1.2\text{ s}$. As to the length of *Game Area* and *Adjusting Area*, we set $G = 100\text{ m}$ and $M = 200\text{ m}$. Each vehicle enters the *Game Area* with a random initial speed around 15 m/s , and the maximum speed limitation is 30 m/s . And, the acceleration of the vehicles is constrained from -3 m/s^2 to 3 m/s^2 .

The simulation of the position, velocity, and acceleration is shown in Figures 6–8. The gaming period ends at the moment when the first vehicle reaches the *Adjusting Area*, and in this simulation, the moment is at 3.12 s . Since salutation of acceleration is not practical, we set the change rate of acceleration (also known as jerk) as 1 m/s^3 . Therefore, there is no abrupt change of acceleration, and the profiles for velocity and trajectory are smooth except the transition moment.

The time-headway of each vehicle passing the merging point is close but not strictly equal, shown in Figure 6, since the velocity of each one at the merging point is different.

As to fuel consumption, we adopt the polynomial model given in formula (8), and it manifests that the instantaneous

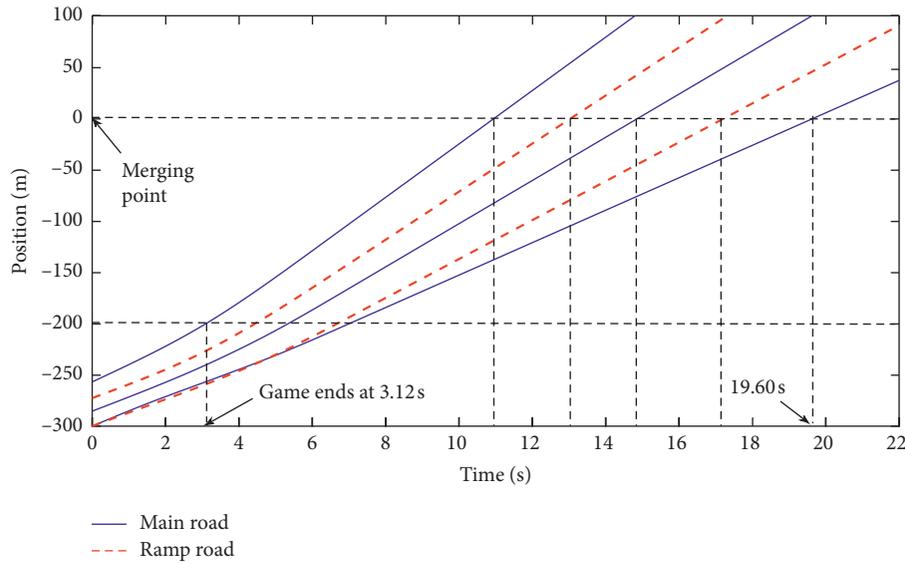


FIGURE 6: Position of vehicles for Case Study 1.

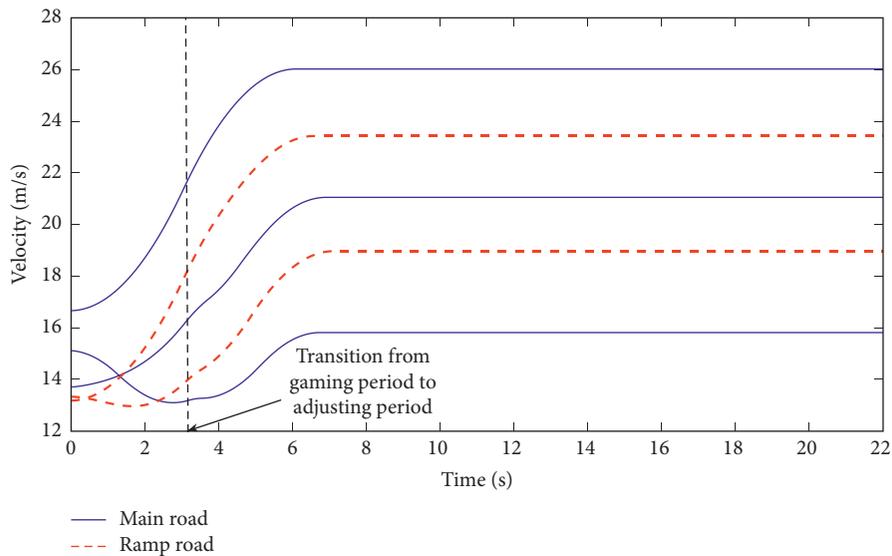


FIGURE 7: Velocity of vehicles for Case Study 1.

fuel consumption depends on the instantaneous velocity and acceleration. We try to compare the fuel consumption between our model and (1) FIFO; (2) Density Prior, and (3) No Control, as shown in Figure 9. Here, “FIFO” is the situation where vehicles that are closer to the merging point are prior to pass the merging point. “Density Prior” is the situation where vehicles on the road with higher traffic density (reflected on the number of vehicles on that road) are prior to pass the merging point and vehicles on the other road should stop to wait until all vehicles on the road with higher traffic density pass the merging point. “No Control” is the situation where vehicles on the ramp road have to stop to wait for vehicles on the main road as they cross the merging point and then start accelerating to reach the maximum speed to pass the merging point.

For FIFO, we initialize all vehicles with the velocity of 15 m/s, and the MS is assigned at $t = 0$ completely based on their distance to the merging point, and other settings are the same as our model. It is, in fact, a special situation of our model where the length of *Game Area* is zero. For “No Control,” we also set the initial velocity of each vehicle as 15 m/s, and in this situation, vehicles on the ramp road must stop to wait until vehicles on the main road passing the merging point. For “Density Prior,” we set the same initial velocity for each vehicle. Since, in this case study, the number of vehicles on the main road is greater than that on the ramp road, the vehicles on the ramp road should also stop to wait until vehicles on the main road pass the merging point. However, in Case Study 2, we discuss and display the situation where number of vehicles on the ramp road is greater than that on the main road.

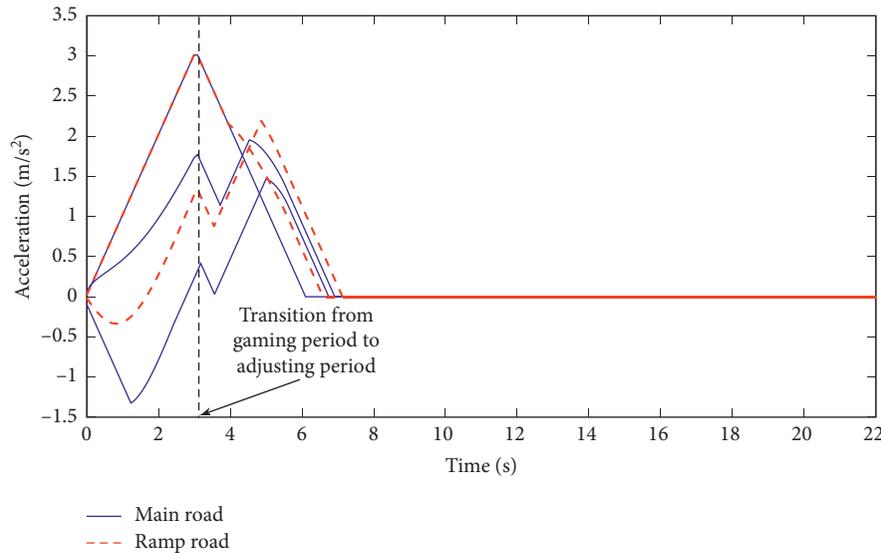


FIGURE 8: Acceleration of vehicles for Case Study 1.

From Figure 9, we can see that the proposed model consumes the least cumulative fuel at the end. However, fuel consumption of the “No Control” model is much lower at the beginning stage since vehicles do not change their states during this period. While fuel consumption of “No Control” model markedly increases in two stages, i.e., the stage in which vehicles on the ramp road slow down and stop and the stage in which vehicles on the ramp road restart and accelerate. Fuel consumption of “Density Prior” is very similar to that of “No Control,” since, in this case study, the number of vehicles on the main road is greater than that on the ramp road, and “Density Prior” and “No Control” are equivalent in this situation.

As to the comparison of the fuel consumption between proposed model and FIFO model, the difference is that there is no *Game Area* in the FIFO model. FIFO is the model that address fairness at the cost of efficiency. Therefore, we can see that the total fuel consumption of FIFO is higher than that of proposed model.

The moment when the last vehicle passing the merging point is the end of the process, and the value of this moment equals the total travel time. And, for this simulation, the total travel time is 19.60 s, shown in Figure 6. The total travel time for the FIFO model is close to the proposed model, but for the “No Control” and “Density Prior” model, it is remarkably higher (about 12% higher) than the other two.

5.2. Case Study 2: “Sliding Window” Parameter $W=10$. In this case study, 10 vehicles are involved in one turn of the game and the number of vehicles on the main road and ramp road is randomly set. Constraints for the vehicles are the same as those in Case Study 1, and some parameters are adaptively changed. We set $G=300$ and $M=200$, and the simulation of the position, velocity, and acceleration is shown in Figures 10–12.

From Figures 10–12, we can see that the vehicles on the main road pay more cost, reflected from the amplitude of variation of acceleration and velocity; because in this

situation, the number of the vehicles on the ramp road is remarkably greater than that on the main road, and the vehicles on the ramp road are dominant as a whole based on the game rules. However, acceptable sacrifice of the disadvantaged group brings the improvement of the efficiency and stability for the whole, and we can see that the variation of the acceleration and velocity of the vehicles on the ramp road (the dominant group) is relatively smoother.

Comparison of fuel consumption among three different models in Case Study 2 is shown in Figure 13. We can see the proposed model still consumes the least cumulative fuel at the end. However, because there exist more vehicles on the ramp road in this case, fuel consumption of the “No Control” model remarkably increased especially during the stage in which vehicles on the ramp road slow down to stop and the stage in which vehicles on the ramp road accelerate. As to the “Density Prior,” vehicles on the main road slow down or stop to avoid collision in this case because number of CAVs on the ramp road is greater than that on the main road. And, we can see that the shape of the fuel consumption curve for “Density Prior” is similar to that of “No Control,” but the cumulative fuel consumption is less since fewer vehicles change their states in the “Density Prior” model than those in the “No Control” model under this case study. Analysis to the comparison between proposed model and FIFO model is similar to that of Case Study 1 and the former still takes advantages than the latter in Case Study 2.

As to total travel time in Case Study 2, it is 35.90 s, shown in Figure 10, and for the FIFO model, it is near to the proposed model. The “No Control” model spends much more time in this case study (about 17% higher than the other two) since the number of vehicles on the ramp road is much greater than that on the main road and the process of slowing down and accelerating to restart takes much time. The proposed model does not take advantage in the total travel time compared with the “Density Prior” model in this case, since the number of vehicles on different roads is unbalanced. “Density Prior” is a model that emphasizes the

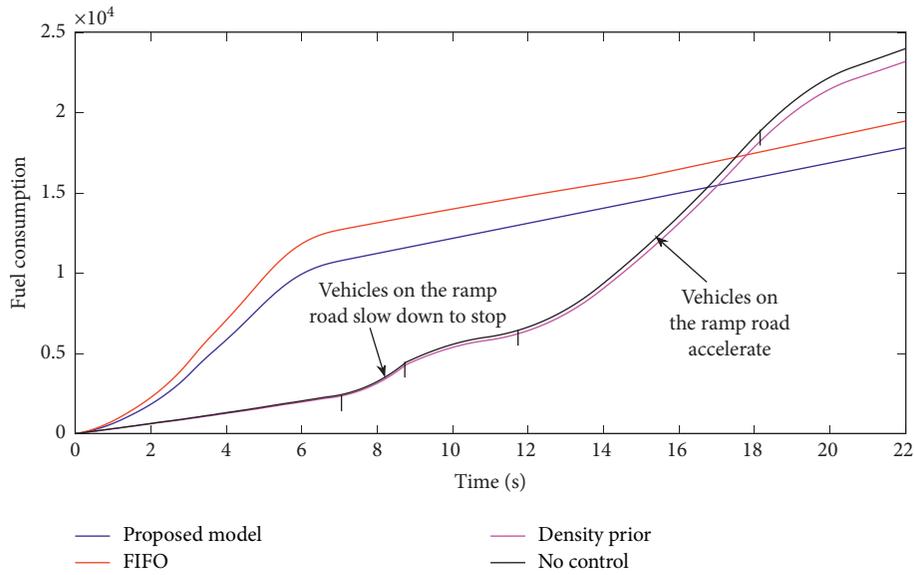


FIGURE 9: Comparison of fuel consumption for different models in Case Study 1.

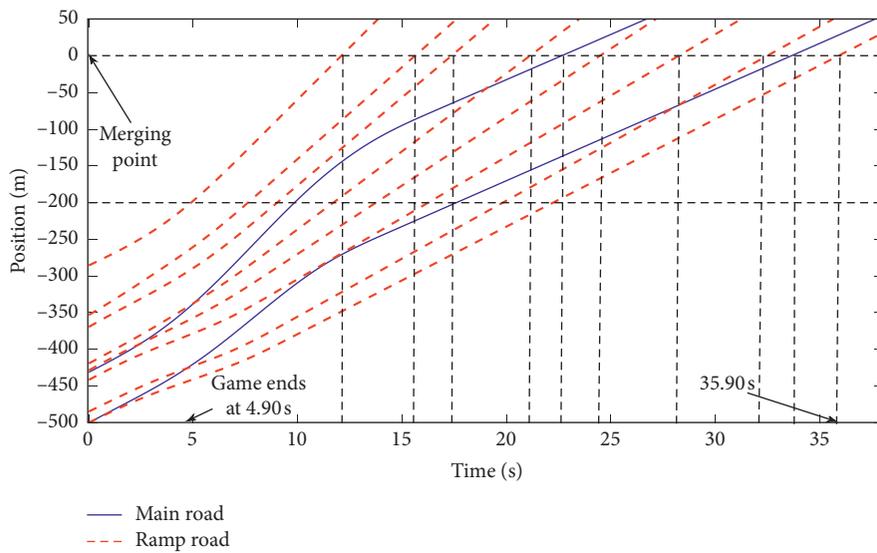


FIGURE 10: Position of vehicles for Case Study 2.

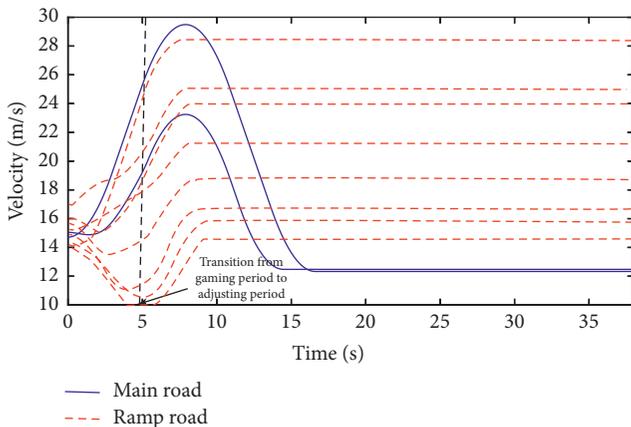


FIGURE 11: Velocity of vehicles for Case Study 2.

efficiency, and it performs well for those circumstances where the traffic density for different roads is extremely unbalanced.

5.3. *Brief Summary of the Simulation Results.* We simulate two cases and validate the effectiveness and efficiency of the proposed model. Case Study 1 mainly focused on the scenario where the number of connected autonomous vehicles is comparatively small in one turn of a game, while Case Study 2 mainly researched the situation where much more agents are involved per round in the game. As mentioned above, FIFO is the model that addresses fairness, while “Density Prior” is a model that emphasizes the efficiency. The proposed model gives consideration to both aspects and performs well.

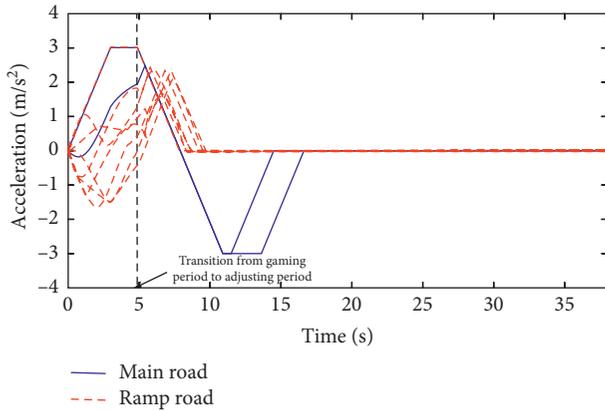


FIGURE 12: Acceleration of vehicles for Case Study 2.

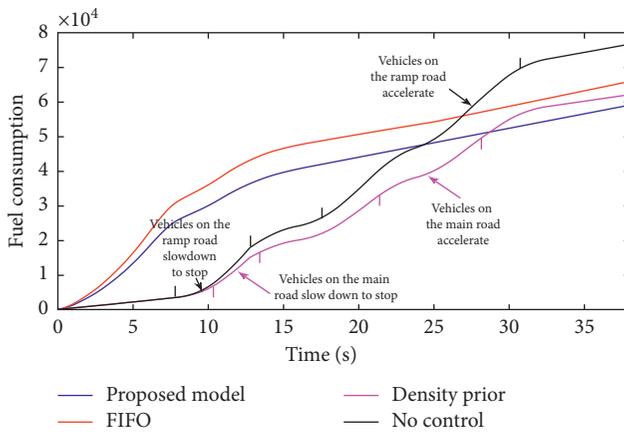


FIGURE 13: Comparison of fuel consumption for different models in Case Study 2.

One thing that should be pointed out is the setting of the parameters M and G . Although we regard the vehicles as mass point, we cannot set M or G as a very small value and settings of these two parameters varies, given different “sliding window” parameter W .

6. Conclusion

In this paper, we focus on the scenario of CAV on-ramp merging where each vehicle is equipped with V2I equipment and can communicate with the centralized controller without any time delay according to the assumption.

The core of the CAVs on-ramp merging problem lies in the assignment of the MS, and different MS leads to the difference on cumulative fuel consumption and total travel time. In our paper, we regard the competition of MS as a game and vehicles on the same road are regarded as a group taking the strategy of cooperation to strive for as small MS as possible against another group. As to the game, we proposed three basic rules in accordance with the Traffic Density Principle, FIFO Principle, and Wholeness Principle, respectively. Further, the control area is divided into *Game Area*, where vehicles on each road change their states cooperatively, attempting to get a better MS, and *Adjusting*

Area, where all vehicles adjusting their states according to the MS are assigned. The game starts at the moment when the last vehicle reaches the *Game Area* (we assume length of the *Game Area* is long enough that all vehicles are still in the *Game Area* when game starts) and ends at the moment when there is a vehicle reaching the *Adjusting Area*.

In both gaming period and adjusting period, IDM is adopted to describe the behavior of the following vehicle and we modify this model, such as adding the constraints of acceleration and velocity, to avoid the abrupt state change at the transition moment. As to the assignment of MS, we evaluate each competitor from three aspects based on the three given rules. To ascertain an optimal weight vector which depicts the influence of each rule, we formulate the problem as a double-objective optimization problem of cumulative fuel consumption and total travel time. Since the relationship between the optimization objectives and the weight vector is unknown, we give different weight vectors as input to search the Pareto Solutions and choose the “inflection point” on the F - T curve as the best fit of our problem. And finally, we search back for the corresponding weight vector as the solution.

Simulation and comparison of the proposed model and other models are conducted and the effectiveness of our model is validated. However, all the results are obtained based on a series of ideal assumption, including no communication, vehicle dynamic delay, etc. Further exploration is needed on the use of feedback control to improve the accuracy, considering the environmental noise and disturbance. Besides, lateral control to the vehicle should also be considered when extending the model to the practical implementation in the future work.

Data Availability

The original codes of the numerical tests used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interests.

Authors' Contributions

Xiangmo Zhao and Haigen Min conceived and designed the research. Xiaochi Li and Runmin Wang performed the experiments. Haigen Min and Yukun Fang analysed the data. Haigen Min and Yukun Fang wrote the manuscript. All authors read and approved the final manuscript.

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