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Research Article

A Cooperative Trajectory Optimization Algorithm for Connected Vehicles in Merging Zones

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Traffic flow optimization and trajectory guidance in merging zones have significant implications for improving capacity and reducing time consumption. The development of V2X communication provides new insights to solve this problem by tackling the information and releasing trajectories schemes. Therefore, this paper aims to discuss the trajectory management in the merging zone for ACC vehicles. A vehicle dispatching and car-following model is proposed to generate steady traffic flow first. An algorithm framework for consecutive traffic flow is presented with the idea of FIFO rules. Then, a two-step method for an individual vehicle is discussed in detail to compute a trajectory. The first step is to select and determine the priority of the optional gaps. The next step is to verify the options' feasibility, decide on the target gap, and output the trajectories to merge successfully. Numerical experiments validate that the proposed method guarantees safe driving and provides relatively smooth trajectories to the vehicles. Furthermore, increased capacity and higher velocity are observed in a comparative experiment. The cooperative optimization algorithm could be applied efficiently in practice and benefit from its rapid response and low computation complexity.

1. Introduction

The traffic organization in merging zones has a significant effect on increasing the efficiency of the bottleneck. Traffic congestion has always been a more frequent problem in merging areas. Several studies have demonstrated that such on-ramp merging often leads to daily traffic congestion, oscillations, pollution, accidents, and even traffic disruptions [1, 2]. Vehicles on the ramp slow down or stop to await a proper opportunity to merge into the main road and hence create a bottleneck and cause congestion. With the rapid development of connected vehicles, V2X communication provides the opportunity for cooperative driving, and some strategies could be proposed to alleviate this problem. Recent studies have investigated the potential benefits of connected vehicle (CV) technology, which may eliminate the critical human factors during the driving process and are expected to improve traffic safety significantly. CVs can reduce the time interval and provide a faster response by determining the appropriate target speed. Therefore, this may improve road traffic safety, efficiency, and stability [3]. The detailed CV technologies can be found in the literature [4]. The main goal of these technologies is to improve security while reducing fuel consumption and traffic congestion. Generally, CVs are divided into adaptive cruise control (ACC), cooperative adaptive cruise control (CACC), and automatic vehicles (AV) with different driving properties. CACC is able to form a platoon and activate a cruise travel mode as a further development of ACC. AVs can instantaneously realize automatic commanding and guiding by central computation, which is the upper level of intelligent vehicles.

In recent years, much attention has been given to the trajectories' optimization in the merging zone. The main idea is to collect information and provide instructions for vehicles to follow and drive safely and smoothly while traveling through the merging zone. However, the strategies

and algorithms utilized in the literature are usually different. According to the different optimization objectives and algorithms, the existing research can be divided into the following three categories:

1.1. Optimization Methods for On-Ramp Vehicles. This category of optimization focuses on the ramp vehicles and proposes signal control methods and optimal algorithms to organize the ramp vehicles' inserting sequences and driving trajectories. Carlson et al. [5–7] adopted a ramp signal control method to optimize the inflow rate of ramp vehicles and evaluate the safe inflow into the main road. Lim et al. [8] proposed a signal control scheme to reduce the overall travel cost and improve vehicles' merging speed, simultaneously setting the minimum delay on the ramp and the outflow on the main road as optimization objectives. Kan et al. [9] constructed an on-ramp flow control approach to organize on-ramp vehicles to the main road to reduce merge collisions and increase driving-out vehicles. Liu et al. [10] proposed a vehicles motion planning algorithm to minimize time-energy cost and alleviate lane congestion caused by on-ramp vehicles so that all vehicles could drive into the merging areas with an optimal trajectory. Letter and Elefteriadou [11] calculated the vehicle's merging sequence by estimating the potential arrival time at the merging point for each ramp vehicle and then optimized the trajectories respectively by adjusting surrounding vehicles' velocities. Zhou et al. [12] presented a trajectory planning strategy for connected automated vehicles to cooperatively execute main line facilitation (i.e., gap development) and on-ramp merging maneuvers. The goal of the optimal trajectory of on-ramp vehicles was to minimize the impact of on-ramp inflow. Chou et al. [13–16] computed the gap in advance by projecting the ramp vehicles onto the main road and determining the vehicles' merging spot and time interval, then provided a speed adjustment strategy for ramp vehicles to guarantee the smooth arrival at the merging point and complete the merging process successfully. Milanes et al. [17] designed a fuzzy controller-accelerator and brake pedal for longitudinal control of on-ramp vehicles under congestion. The controller avoids traffic congestion by adjusting the speed of on-ramp vehicles to allow them to drive into the main road fluidly and smoothly.

1.2. Optimization Methods for Main Road Vehicles. In order to allow the ramp vehicles to drive into the main road smoothly, the main road vehicles can generate appropriate gaps beforehand through related vehicles' acceleration or deceleration or changing lanes [18, 19]. Scarinci et al. [20] presented a novel merging strategy that exploited the communication capabilities of intelligent vehicles. The proposed method requires the cooperation of equipped vehicles on the main carriageway to generate merging gaps and compute trajectories for on-ramp vehicles released by traffic lights. Subraveti et al. [21] proposed a rule affecting the longitudinal behavior of vehicles on the main road, which mainly aimed to optimize the expected speed and total travel time with the maximum speed constraints. The foundational idea of the algorithm was to generate sufficient gaps by affecting the fewest vehicles. Pueboobpaphan et al. [22] proposed a decentralized merging supported strategy for heterogeneous vehicles that aimed to improve the stability of traffic flow around the merging area by reducing conflicts and limiting speed variations. The solution was to provide smooth deceleration schemes for the upstream arterial vehicles in the merging area to generate gaps for on-ramp vehicles by identifying and forecasting the speed and position of on-ramp vehicles. Cao et al. [23] introduced state variables of the modified trajectory of the main road vehicles to the optimization problem, by which the merging point of the merging vehicle is optimized according to the motions of the main lane vehicles. Davis [24] proposed an algorithm to adjust the vehicles' speed on the main road with the preceding vehicles on the current and target lanes simultaneously. This method guarantees sufficient gaps for ramp vehicles in advance with the ACC vehicles' communication and ensures the vehicles drive into the main road successfully at the merging spot. Park et al. [25] presented a different solution in which the vehicles on the main road changed lanes to provide enough space for ramp vehicles in the merging area. This algorithm calculates and estimates the anticipated lead-lag gaps with three dynamic motions (accelerating, maintaining current speed, and decelerating) and then provides lane-change advisories to freeway main-line vehicles that cooperate with the anticipated gaps. Wang et al. [26] proposed two novel ramp merging algorithms for sensor-enabled cars. Algorithm 1 computes the "smoothest" speed adjustment for vehicles on the main road and an optimal merging point for a ramp vehicle. Algorithm 2 increases the tolerance for sensor information by restricting the impact of merging to a small group of main road vehicles.

1.3. Cooperative Optimization for On-Ramp and Main Road Vehicles. This algorithmic category paid attention to cooperative optimization and could be further divided into optimal control and feedback control. The optimal control is aimed at organizing the total passing time of vehicles, average speed, acceleration, fuel consumption, and so on. Rios Torres and Malikopoulos [3] address the problem of optimally coordinating CAVs at merging roadways to achieve smooth traffic flow without stop-and-go driving and present an analytical closed-form solution that allows online coordination of vehicles at merging zones. Xu et al. [27] proposed a collaborative inflow control strategy to determine vehicles' sequences and trajectories. Intending to minimize the vehicles' total speed fluctuation, the proposed trajectory planning algorithm constructed a classical variational and quadratic programming method to obtain the expected arrival time, optimal inserting time, and other corresponding variables needed to decide the vehicles' trajectories. Min et al. [28] presented a global optimization framework for CAVs based on game theory, in which the priority of vehicles passing intersections was evaluated in accordance with traffic density, fairness, and wholeness. Xie et al. [29] sorted the vehicles' sequence by the predicted time

spot when the vehicles arrived at the merging area and coordinated the vehicles' velocities with safe gaps and acceleration constraints. Then, a longitudinal merging control algorithm is used to maximize the average speed. Awal et al. [30] proposed a proactive optimal merging strategy that dissociates the point of decision-making from the actual merging point. Based on various merging situations, the vehicles are divided into different groups, and the optimal merging sequence is computed according to the driving information of the leading vehicle and shared with the vehicles in the identical group. Then, the vehicles adjust their velocities to guarantee safe distance and reduce the merge delay. Ntousakis et al. [31] established a vehicle longitudinal trajectory optimization model with the objectives of maximizing energy efficiency and driving comfort, and then realized the optimal speed organization by minimizing the acceleration and velocities' first and second derivatives.

The core idea of feedback control is to project the vehicles on the ramp onto the main lane to form a virtual vehicle queue. Therefore, the on-ramp vehicles' merging organization could transform into a car-following problem with safety and kinematic constraints [32, 33]. Chen et al. [34] introduced a virtual rotation strategy to project the vehicles on the main road and the ramp onto a shared straight axis simultaneously and transformed the merging problem into a virtual car-following problem to reduce the complexity and dimensionality. Then, a distributed feedback and feedforward longitudinal scheme is developed to actively generate gaps for vehicles by managing acceleration, speed, position, and energy. Lu and Hedrick [35] mapped the merging vehicle to the middle position between two adjacent vehicles on the main lane, and the merging vehicle must arrive at the merging point at the proper time by adjusting velocity through acceleration or deceleration before driving out. Huang et al. [36] proposed a cooperative merging strategy that projected vehicles on the ramp onto the main road to form a virtual vehicle platoon, and a bidirectional communication topology was used to achieve the vehicle intercommunications. Furthermore, a distributed controller based on the feedback linearization method was designed to ensure inner-vehicle closed-loop stability for the virtual platoon with derived feedback gains. Zhou et al. [37] put forward the cooperative trajectory optimization problem for ramp vehicles, and a feedback controller is designed to control the motion of the main road vehicle and ramp vehicle and ensure the vehicles complete the combined operation smoothly.

In summary, the research and discussion of ramp vehicles' merging problem mainly focused on the signal control of ramp vehicles as well as the optimization of vehicle driving speed, inflow sequence, trajectory, and the speed control optimization of main road vehicles. Although some researchers have discussed the collaborative optimization control algorithms, the main idea is to form a virtual queue of the ramp and main road vehicles and then transform it into a car-following or optimization problem. The existing methods have some disadvantages in entirely using the vehicle-to-infrastructure cooperative technology. Some studies only provided an algorithm to generate sufficient merging distance in advance by driving after two preceding vehicles simultaneously. However, predicted vehicles' trajectories and the central-control and comprehensive communication are needed to develop further. Therefore, to improve the safety and efficiency of the on-ramp merging process, this paper proposes a cooperative optimization method for connected vehicles on the basis of previous studies. Based on the improved car-following model, a merging control method for on-ramp vehicles is proposed to achieve the safe and efficient merging of ramp vehicles in the connected environment. Connected vehicles receive real-time traffic information from vehicle-to-infrastructure technology and then predict the driving status of surrounding vehicles. Furthermore, a speed guidance method to ensure the successful merging of the ramp vehicles is presented in detail. In addition, the main contributions of this paper are listed as follows:

(i) An improved vehicle dispatching and car-following model have been presented for connected environments. It is applicable for different traffic states and can describe driving behaviors in congested or free flow. The merging optimization algorithm is based on the driving models to generate stable traffic flow;

(ii) An organization framework for consecutive traffic and a trajectory scheduling method for one individual vehicle have been implemented separately. The optimization sequence and cooperative strategies for commutation between vehicles and the central unit have been proposed and explained explicitly;

(iii) For each vehicle, a method for inserting gap selection, priority provision, and feasibility validation for each gap through computing the cooperative trajectories has been presented in detail.

The remainder of this paper is organized as follows: Section 2 presents improved vehicle dispatching and car-following models with various vehicle gaps. In Section 3, an organization framework for consecutive traffic is proposed to describe the cooperative strategies. Section 4 explains the trajectory optimization process for one single vehicle. Then, Section 5 summarizes the results of a numerical experiment and discusses the results of a controlled experiment designed to verify the algorithm's effectiveness. Finally, Section 6 summarizes the findings, implications, and limitations and suggests some future research directions.

2. Traffic Modeling Framework for Connected Vehicles

The models for connected vehicles' driving behavior can be divided into two categories. One is a manual car-following model for ACC vehicles. In this mode, driving information is issued to aid in deciding trajectories, and the car-following model is calibrated with NGSIM data. The other is a cruise mode for CACC in which connected vehicles form an ordered platoon complying with some particular rules, and the

following vehicles turn on the cruise mode with the head vehicle. In this paper, the vehicles in the network are considered ACC vehicles. The main purpose is to optimize on-ramp vehicles' trajectories, and smooth driving lines for vehicles are expected to be completed safely and efficiently. The optimization algorithms proposed in this paper are mainly applicable for manual-driving vehicles in connected conditions. A central processor in the ramp zone will collect information, optimize trajectories, and issue the optimal strategy to the connected vehicles.

The entire framework includes microscopic dispatching models at the entrance spot, car-following behaviors on en-route lanes, and optimized ramping strategies to further describe the connected vehicles' behaviors in a special ramp zone. A Poisson flow distribution, detailed in Section 2.1, is applied to dispatch the vehicles based on the car-following model from NGSIM data, and an improved model structure for unsaturated and oversaturated flow is modified to describe various circumstances. Moreover, the core ramping strategies are explained in the remaining sections.

This paper incorporates a network consisting of the main road and a ramp lane. The time horizon T is divided into identical segments denoted by k with an interval's duration of $\Delta t\,(k = 1, 2 \ldots K)$.

2.1. Microscopic Dispatching Models for Driving-in Traffic Flow. The microscopic dispatching model aims to generate a steady traffic flow with safety and capacity constraints. The preconditions of this model are described as follows:

(1) All the controlled vehicles are in ACC mode and are enabled to communicate with each other. In particular, in the controlled zone, all vehicles will receive and accept guidance from the central processor.

(2) In order to comply with the traffic flow distribution in the real world, the vehicles are adjusted to follow a Poisson distribution, arriving at the beginning spot of the research zone. The time interval for the two successive vehicles follows a negative exponential distribution. The mean value of the interval is the inverse of traffic volume per unit of time. It should be noted that a time interval smaller than the minimum reaction time is not permitted in the initial stochastic traffic flow, and the vehicles will wait for a sufficient time gap in this situation. In the simulation section, a group of pseudo-random integral numbers following a negative exponential distribution will be generated to record the arrival time of vehicles.

(3) If the traffic demand is smaller than the lane's capacity, the vehicles are enabled to drive into lanes, and a safety gap could be guaranteed simultaneously. However, in oversaturated cases, the exceeding vehicles will form a queue at the initial spot, and the vehicles will enter one by one to ensure a minimum safety distance. In this article, we dispatch the vehicles with FIFO rules, and the queue length will be ignored. In the simulation, if the time gap is smaller than the reaction time, the vehicles will postpone the arrival time to form a queue and drive into the lane one by one.

2.2. Vehicles' Driving Models. The vehicles' driving models aim to calculate the position and speed along with the timeline. A driving strategy is necessary to describe vehicles' behaviors in the whole zone after dispatching the vehicles at the beginning of the lanes. A universal connected car-following model proposed by PATH Laboratory in the United States [38] can be found,which is applicable for high-volume traffic flow. However, when the distance between vehicles exceeds the communication range, the connected vehicles could perform as human-driven ones. The successive vehicles will accelerate to reduce the gaps without safety constraints until reaching a short enough distance. After entering into communication range, a trajectory strategy will be applied to approach the frontier vehicle in the shortest time possible. Finally, a connected car-following model is practical to describe behaviors in the safety gap. Therefore, in this article, three driving modes for different vehicle distances are presented as the following cases:

(1) Case 1: defined as free-flow mode, satisfied $S_{i-1}(t) - S_i(t) \geq L_1$. $S_i(t)$ is the vehicle's position at time t, $S_{i-1}(t)$ is the preceding vehicle's position; parameter L_1 is the maximum distance able to communicate, defined by the vehicle and roadside sensor equipment.

This process will occur when the preceding vehicle is beyond the communication range. Similar to manual vehicles, connected ones will speed up under kinematic restraints. Then, the equations will be written as follows:

$$\begin{aligned} a_i(t) &= \min\left(a_{\max}, f_1 * \left(v_{\max} - v_i(t)\right)\right), \\ v_i(t) &= \min\left(v_{\max}, v_i(t-1) + a_i(t-1) * \Delta t\right), \end{aligned} \tag{1}$$

where a_i and v_i are, respectively, the acceleration and speed of a vehicle i at time interval t; $a_{\max}$ and $v_{\max}$ are, respectively, the maximum acceleration and speed; f_1 is the free acceleration rate for vehicles.

In the above equations, the vehicle movements are determined by kinematic parameters not restricted to other vehicles.

(2) Case 2: defined as approximation mode, satisfied $L_2 \leq S_{i-1}(t) - S_i(t) < L_1$. Accordingly, the space between two adjacent vehicles belongs to the half-closed interval of $[L_2, L_1)$.The parameter L_2 presents a proper distance at which vehicles can communicate with each other and intends to reduce the gap to a safety value in the shortest time.

Several studies in the literature have focused on this process. Some researchers have discussed how connected vehicles can follow central instructions to find an optimum trajectory and form a stable traffic flow in the shortest time. Nevertheless, in

this article, more concerns are concentrated on the congested merging zones; hence, cases 1 and 2 for low volumes will occur with a lower probability. This process is applied to generate a stable traffic flow before the merging spot, so a detailed optimum strategy is neglected in this part.

The preceding vehicle has limited impacts on the current vehicle in this case. The acceleration and speed of vehicle i can be computed as

$$a_i(t) = \min\left(a_{\max}, f_2 * h_i(t-1) + f_3 * \left(v_{i-1}(t) - v_i(t)\right)\right), \tag{2}$$

$$\begin{aligned} h_i(t) &= S_{i-1}(t) - S_i(t), \\ v_i(t) &= v_i(t-1) + a_i(t-1) \times \Delta t. \end{aligned} \tag{3}$$

In these equations, $h_i(t)$ is the headway at time t. (2) states that acceleration is positively correlated with the headway and the speed difference. f_2 and f_3 are weight parameters. The driving behavior described in these expressions conforms to human-driving habits and vehicles' kinematic constraints.

(3) Case 3: defined as the car-following mode for close distance. The vehicle is close enough to the preceding vehicle and is greatly affected by the front vehicle, and the headway satisfied $S_{i-1}(t) - S_i(t) < L_2$. For this case, the car-following strategy proposed by PATH Laboratory is presented to describe the vehicle's behavior. This model guarantees collision avoidance and constructs the expression of the gap error and the velocity to decide the vehicles' movements.

$$\begin{aligned} e_i(t) &= h_i(t-1) - t_r \cdot v_i(t-1), \\ v_i(t) &= v_i(t-1) + e_i(t) \times f_4 + \\ &\quad \left(\frac{\mathrm{d}\left(e_i(t)\right)}{\mathrm{d}t}\right) \times f_5. \end{aligned} \tag{4}$$

In which $e_i(t)$ denotes the error between the actual and expected intervehicle space at time t; t_r is a comfortable and safe response time of connected vehicles; f_4 is coefficient of vehicle distance $e_i(t)$; f_5 is coefficient of vehicle distance differential.

3. Framework of the Collaborative Merging Algorithm

3.1. Hypothesis on Connected Vehicles and Roadside Communication Infrastructures. Driving behaviors have essential significance, especially in a congested merging zone. For traditional intersections, manual vehicles adjust speed to insert into the nearest gap with enough safe distance while the information on the main road is gathered by users' observation in a visual range. Due to the vehicles' heterogeneous decisions and the lack of communication, no guarantee can be made that the vehicles could insert into the main road without waiting or colliding. The crucial issues are to find an optimal gap in advance and decide trajectory guidance for vehicles to drive into the selected gap with safety constraints in the merging zone. The main objective is to obtain low time costs, high-speed stability, and driving safety. Connected vehicles can realize an optimum collaborative merging process using V2X communication.

A merging zone with one ramp lane is shown in Figure 1. Not considering consecutive lane changes, one lane on the main road is presented in the algorithm to simulate the vehicle's lane change in the merging zone. As depicted in Figure 1, spots A and B are denoted as the starting spots of the detecting area on the two lanes, and the optimized strategy will be issued to vehicles from these spots. L_c is the distance to the merging point, L_a represents the length of the auxiliary lane in which ramp vehicles are permitted to change lanes.

The detection and central computation will be activated when the vehicles on the ramp arrive at spot A. A target gap on the main road is checked and selected first, and the range for searching gaps is defined in Figure 1. Then, an optimal gap is chosen for ramp vehicles, and the computed trajectories will be transmitted to the related cooperative vehicles. The fundamental goal of the algorithm is to avoid collisions and improve traffic efficiency while all vehicles are forced to satisfy safety and kinematic restraints. The optimization strategy aims to guide the vehicles to successfully insert into the main road traffic, and the algorithm solution includes merging time and spot and vehicles' position and speed over the time zone.

All ACC vehicles can communicate and exchange information such as position, speed, and acceleration. In addition, the vehicles are supposed to receive and accept the command signal from the central unit and follow the instructions.

3.2. Cooperative Merging Process for Consecutive Traffic Flow. In the proposed method, the vehicles are organized and issued with cooperative merging strategies, complying with FIFO rules. The flowchart of the traffic flow process for all vehicles at consecutive times is explained in detail in Figure 2. As depicted in this figure, the generated traffic

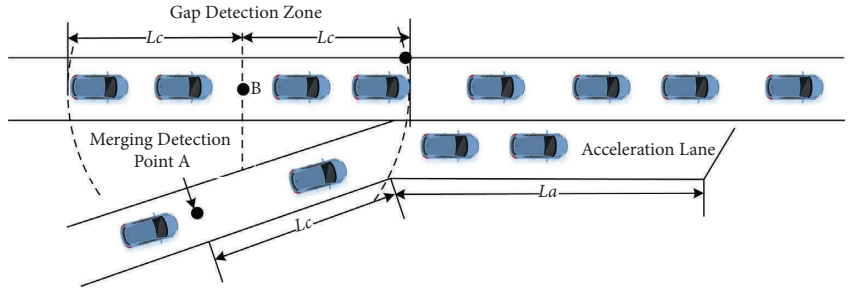

Figure 1: Description of the network.

flow drives on the lanes that comply with the models in Section 2. If a vehicle j arrives at the detection spot, the cooperative merging algorithm is activated in the computer, and the trajectories of preceding vehicles stored in the central unit are the essential information to make strategies for subsequent vehicles. Eventually, if vehicles $j-1$, $j-2$, and others still drive on the ramp or auxiliary lane, a safety distance must be satisfied.

Therefore, the algorithm is executed repeatedly in the simulation time interval, and the other vehicles besides the optimized collaborative vehicles drive to comply with the ACC car-following model. The velocity fluctuation of vehicles driving out of the lane will be recorded to verify the effectiveness of the algorithms.

4. Trajectory Optimization for One Single Merging Vehicle

The unresolved key issue with the framework of the cooperative process for consecutive traffic flow is to program trajectories in the defined merging zone for each vehicle with a series of objectives and constraints. It is evident that the total number of vehicles traveling through the merging point in a certain time is an essential goal where collision avoidance and vehicle kinematics are constraints. Two-stage cooperation merging trajectory optimization for each vehicle on-ramp is discussed in this paper. The first stage is to determine the proper inserting gap with some proposed rules. The second stage is to compute a trajectory throughout the process and provide the insertion time and spot to the central system. Actually, the first stage defines the associated vehicles and the optimization objectives, and the second stage aims to achieve the goal through speed adjustment with the associated vehicles. The characters of this method concentrated on the optimization one by one, and just two cooperative vehicles were needed to keep in communication and follow the systems' instructions. It is easily realizable in the early days of automatic vehicles.

4.1. Selection Strategies for Inserting Gaps. In this stage, proper gaps in the designated area for vehicle inserting will be computed, and a group of gaps will be recommended in a priority order, which will be validated to determine the ultimate feasible inserting gap and the driving trajectories at the second stage.

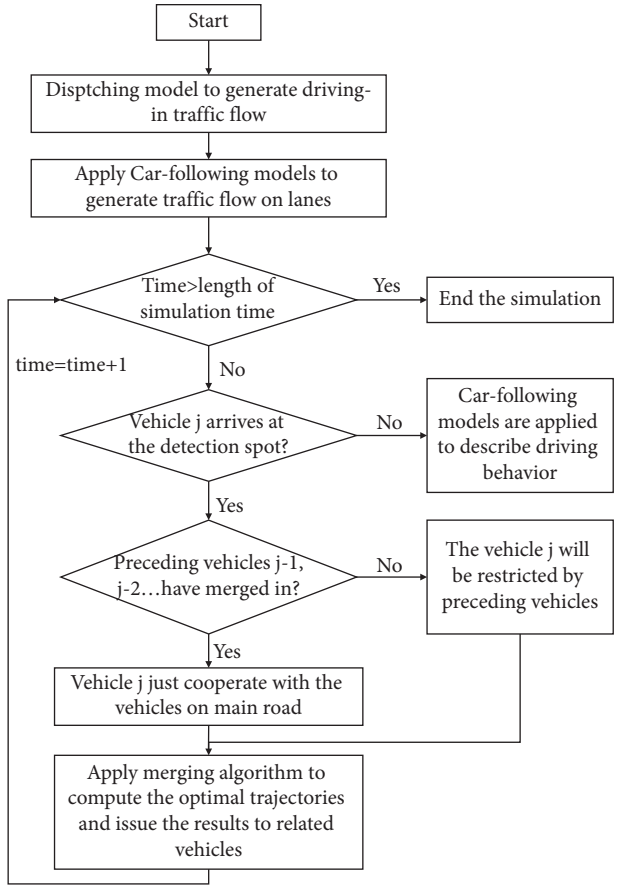

Figure 2: The algorithm's flowchart of consecutive traffic flow.

When vehicle j on the ramp arrives at the detection point, the gap-selection algorithm will be activated. The main idea is to check if the vehicle is enabled to insert into the selected gap. The entire algorithm can be explained as follows:

(1) Define the alternative sets primarily as follows: check and record the vehicle i on the main road around the mapping point B and consider the detection range as L_c (as explained in Figure 1), which means the far gaps beyond the range along with long-time speed adjustment are not considered. The parameter L_c remarkably affects the effectiveness and complexity of the algorithm. A

general maneuver is implemented in practical application to maximize L_c in allowed computation time.

Detect the vehicles' information in the range and record the position $s_i(t)$ and velocity $v_i(t)$. A set $S = \{s_i(t), s_{i+1}(t)\ldots\}$ is introduced to evaluate the position of the vehicle i. The gap between adjacent vehicles can be eventually calculated and denoted as a set $G = \{g_i(t), g_{i+1}(t)\ldots\}$, in which $g_i(t) = s_{i-1}(t) - s_i(t)$. Therefore, all the gap alternatives are included in set G. Further work is needed to check the feasibility of alternatives and provide orders with priority.

For collision avoidance, the minimum safety distance between adjacent vehicles $h_s(t) = v_i(t) \times t_r$ is determined by the speed of successive vehicles $v_i(t)$ and reaction time t_r. Therefore, the minimum length of a feasible gap that is permitted to insert one more vehicle can be expressed as $g_m(t) = L + 2 \times h_s(t)$, in which L is vehicle's length. A foundational idea is to prioritize the alternatives with enough distance to ensure a smooth entry without speed fluctuations.

(2) Further check for alternatives without speed adjustments: this step aims to estimate whether the current vehicle j can successfully merge into a chosen gap before reaching the end of the acceleration lane without speed adjustments.

If the gap i is suitable for vehicle inserting without speed adjustment, position $s_j(t')$ needs to be precisely mapped to the gap i on the main road, and the vehicles' distance has to meet the safety requirements. In addition, position $s_j(t')$ is restrained in the range of the acceleration lane and forbidden to drive out. Consequently, the followingequations are constrained to be satisfied:

$$s_i(t') + h_s(t') \le s_j(t') < s_{i-1}(t') - h_s(t'), \tag{5}$$

$$2 \times L_c < s_j(t') < 2 \times L_c + L_a. \tag{6}$$

In the above expressions, t' represents the inserting time, and the position $s_j(t')$ and $s_{i-1}(t')$ can be easily evaluated with a constant velocity.

(3) Ordering rules for alternative gaps: the essential purpose of this algorithm is to diminish velocity's fluctuation, and hence the gaps with enough space will have priority. Firstly, the alternatives are categorized into three subsets.

If $g_i(t) > g_m(t)$, it indicates that the gap i has enough distance to accommodate a vehicle to insert directly. Furtherly, two subsets $G_s(t)$ and $G_u(t)$ are introduced to distinguish the alternatives, $G_s(t) = \{g_i(t) | g_i(t) > g_m(t)\}$, and the remaining belong to $G_u(t)$.

$G_s(t)$ and $G_u(t)$ are furtherly split into two subsets separately along with different gap positions.

$$\begin{aligned}
G_s(t) &= \{G_{sf}(t), G_{sb}(t)\},\\
G_u(t) &= \{G_{uf}(t), G_{ub}(t)\},\\
G_{sf}(t) &= \{g_i(t) | g_i(t) > g_m(t) \& s_i(t) > s_j(t)\},\\
G_{sb}(t) &= \{g_i(t) | g_i(t) > g_m(t) \& s_i(t) < s_j(t)\},\\
G_{uf}(t) &= \{g_i(t) | g_i(t) \le g_m(t) \& s_i(t) > s_j(t)\},\\
G_{ub}(t) &= \{g_i(t) | g_i(t) \le g_m(t) \& s_i(t) < s_j(t)\}.
\end{aligned} \tag{7}$$

Based on these equations, the ordering rules for alternative gaps are described in the flowchart in Figure 3. First, the foundation idea is to give priority to the gaps in $G_s(t)$ which have the opportunity to insert without velocity fluctuation. Furthermore, alternatives in $G_{sf}(t)$ deserve priority over those in $G_{sb}(t)$ because the front gap can force the vehicle j to achieve a higher speed and reduce total travel time. Second, in an identical subset, the gaps will be verified in terms of distance to the vehicle j until an optimal gap can be chosen or all the options are checked. Last, (5) and (6) are essential requirements to ensure direct insertion. If all the alternatives in $G_s(t)$ are not able to provide trajectories to satisfy constraints (5) and (6), a merging method with cooperative velocity guidance detailed in Subsection 4.2 will be imposed.

4.2. Merging Method with Cooperative Velocity Guidance. Suppose no alternative gaps can satisfy an extra vehicle to insert without speed fluctuations. In that case, this algorithm will be activated to provide a trajectory through cooperative velocity guidance and issue detailed information, including merging position, merging time, and velocity, to the central system. The basic idea is to verify the gaps' feasibility one by one in order of distance, if $g_i(t) \in G$ is chosen, the associated vehicle i on the main road and vehicle j on the ramp will receive velocity guidance, and other vehicles will keep on car-following driving with natural properties. Firstly, a safe gap will be guaranteed by a comfortable deceleration d_c of vehicle i, and then the minimum deceleration time t_i^d will be computed as

$$\begin{aligned}
\Delta g_i\left(t + t_i^d\right) &= 0.5 d_c \cdot \left(t_i^d\right)^2,\\
\Delta g_i(t) &= g_m(t) - g_i(t).
\end{aligned} \tag{8}$$

In which t_i^d can be evaluated by

$$t_i^d = \sqrt{\frac{2\left(g_m(t) - g_i(t)\right)}{d_c}}. \tag{9}$$

In time interval $[t, t + t_i^d]$, vehicle i slows down to enlarge the distance from the preceding vehicle $i-1$. The trajectory is decided by velocity $v_i(t + \Delta t)$ and position $s_i(t + \Delta t)$ as expressed in equations (10)–(12). Once the deceleration is finished, vehicle i will drive at a steady speed $v_i(t + t_i^d)$ until vehicle j ramps into the chosen gap successfully. Furthermore, vehicles not participating the cooperation maneuvers will drive with the car-following model.

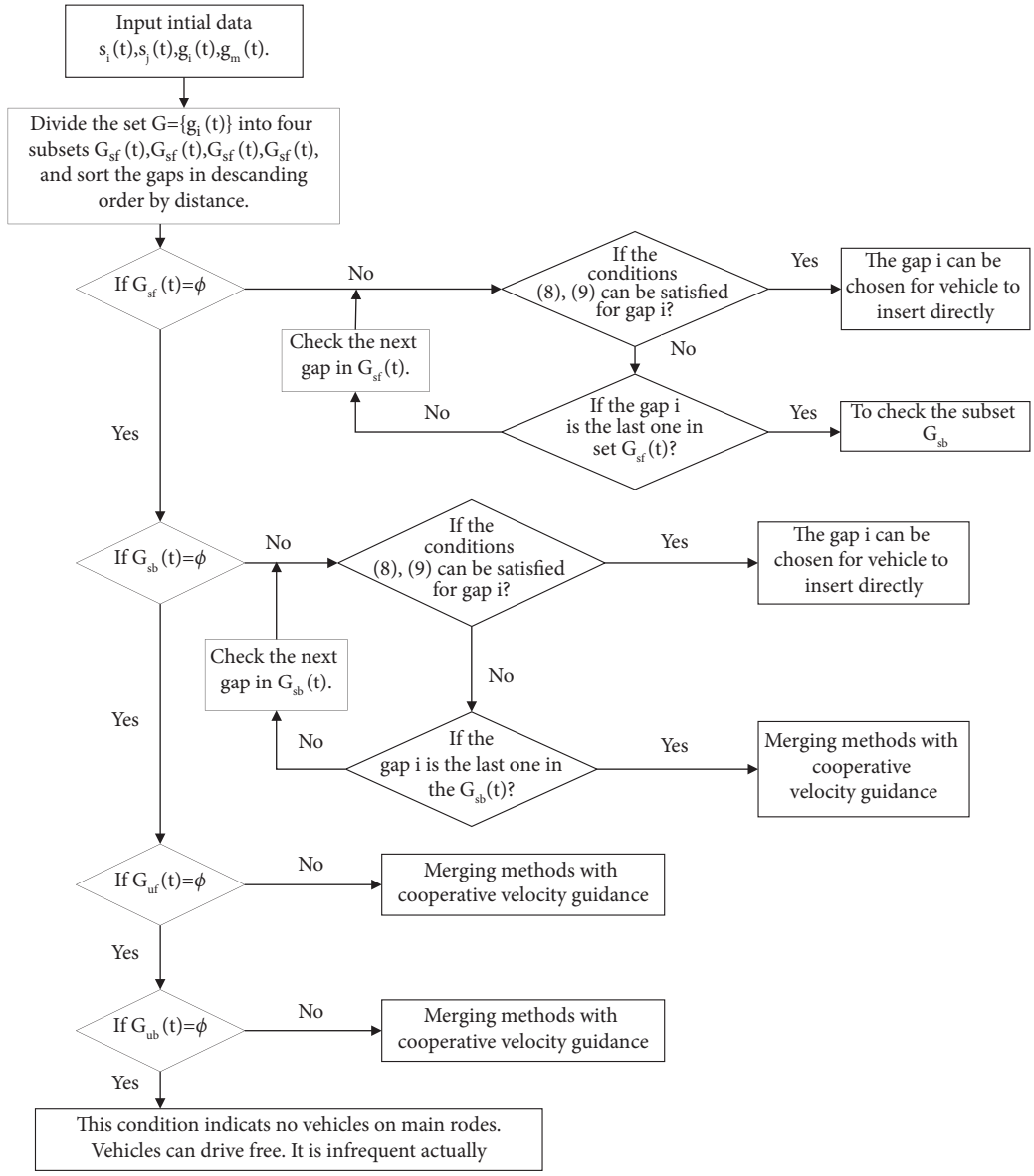

Figure 3: The flowchart of the gap selection process and priority for different subsets.

$$v_i(t+\Delta t) = v_i(t) - d_c \cdot \Delta t, \quad \left(0 \le \Delta t \le t_i^d\right), \tag{10}$$

$$v_i\left(t+t_i^d\right) = v_i(t) - \sqrt{2d_c \cdot \left(g_0(t) - g_i(t)\right)}, \tag{11}$$

$$s_i(t+\Delta t) = s_i(t) + \sum_{\Delta t=1}^{t_i^d} v_i(t+\Delta t), \quad \left(0 \le \Delta t \le t_i^d\right). \tag{12}$$

A preprogrammed trajectory is required to satisfy constraints (5) and (6) and guarantee a safe distance to the preceding vehicle $j-1$. A particular scenario exists in which the vehicle $j-1$ has entered the traffic on the main road, and an unconstrained movement on the ramp can be planned. Therefore, multiple cases divided by different traffic statuses are proposed to constitute the comprehensive trajectory optimization process. The detailed algorithm is displayed in the flowchart of Figure 4, and the following assumptions are considered in the algorithm idea: (1) throughout the whole process, a constant acceleration or deceleration is needed to avoid drastic fluctuation, and (2) the maximum speed $v_{\max}^m$ on the main road is designed to be larger than $v_{\max}^r$ on the ramp.

(1) Case 1 (corresponding to algorithm 1): this case occurs when the preceding vehicle $j-1$ has merged into the main road and does not influence the movements of vehicle j at time t_j. We denote vehicle j that can merge into main road at time t_j^m, then vehicle j speeds up or down during time interval of $[t_j, t_j + t_j^{h_1}]$ and drives with a constant velocity for

the period of $t_j^{h_2}$. Generally, if $g_i(t_j) \le s_j(t_j)$, and the chosen gap is ahead, vehicle j will speed up; otherwise, it will make a deceleration. The following criteria are needed to be satisfied:

$$s_j\left(t_j^m\right) \ge s_i\left(t_j^m\right) + h_s\left(t_j^m\right), \tag{13}$$

$$t_j^{h_1} + t_j^{h_2} = t_j^m - t_j, \tag{14}$$

$$s\left(t_j + t_j^{h_1}\right) = s_j\left(t_j\right) + v_j\left(t_j\right) \times t_j^{h_1} + a_j \times \frac{\left(t_j^{h_2}\right)^2}{2}, \tag{15}$$

$$v_j\left(t_j + t_j^{h_1}\right) = v_j\left(t_j\right) + a_j \times t_j^{h_1}, \tag{16}$$

$$0 \le v_j\left(t_j + t_j^{h_1}\right) \le v_{\max}^r \tag{17}$$

$$s_j\left(t_j^m\right) = s_j\left(t_j + t_j^{h_1}\right) + v_j\left(t_j + t_j^{h_1}\right) \times t_j^{h_2}, \tag{18}$$

$$s_i\left(t_j^m\right) = s_i\left(t_j + t_i^d\right) + v_i\left(t_j + t_i^d\right) \times \left(t_j^h - t_i^d\right), \tag{19}$$

$$L_c \le s_j\left(t_j^m\right) - s_j\left(t_j\right) \le L_a + L_c, \tag{20}$$

$$h_s\left(t_j^m\right) = v_i\left(t_j + t_i^d\right) \times t_r. \tag{21}$$

(2) Case 2 (corresponding to algorithm 2): this case occurs when preceding vehicle $j-$ has not finished the merging optimization, and the trajectory of vehicle j will be restricted to maintain a safe distance. In this situation, vehicle j will follow the preceding vehicle first and then change velocity to cooperate with the target gap.

A noticeable phenomenon is that vehicle j can finish this process before time t_{j-1}^m on the auxiliary lane. For this situation, a car-following behavior is managed for vehicle j during the time $[t_j, t_j^m]$ to cooperate with the speed adjustment of vehicle i on the main road. Similarly, the constraints needed to be satisfied are listed as follows:

$$\begin{aligned}
&s_j\left(t_j^m\right) \ge s_i\left(t_j^m\right) + h_s\left(t_j^m\right),\\
&s_j\left(t_j^m\right) = s_{j-1}\left(t_j^m\right) + v_j\left(t_j^m\right) \times t_r,\\
&s_i\left(t_j^m\right) = s_i\left(t_j + t_i^d\right) + v_i\left(t_j + t_i^d\right) \times \left(t_j^h - t_i^d\right),\\
&L_c \le x_j\left(t_j^m\right) - x_j\left(t_j\right) \le L_a + L_c,\\
&h_s\left(t_j^m\right) = v_i\left(t_j + t_i^d\right) \times t_r,\\
&t_j^m \le t_{j-1}^m.
\end{aligned} \tag{22}$$

(3) Case 3 (corresponding to algorithm 3): another opposite situation is that vehicle j cannot merge into the chosen gap in the period of $[t_j, t_{j-1}^m]$. A remarkable scene could appear in the process. If the vehicle trajectory programmed without preceding vehicle $j-1$ can guarantee a safe distance throughout the whole process, algorithm 1 in case 1 (depicted in expressions (13)–(21)) will be initiated to compute the trajectory. This state is possible when a minor acceleration or deceleration is planned for vehicle j in algorithm 1, and the gap between adjacent vehicles on the ramp will enlarge. Therefore, three substeps are presented if the preprogrammed trajectory by algorithm 1 collides with vehicle j at time $t_j^{h_0}$.

Step 1: In time interval $[t_j, t_j^{h_0}]$, coincide with the preprogrammed trajectory by algorithm 1. Note that if a feasible solution cannot be found by algorithm 1, this step will be deleted.

Step 2: In time interval $[t_j^{h_0}, t_{j-1}^m]$, follow with the vehicle $j-1$.

Step 3: In time interval $[t_{j-1}^m, t_j^m]$, coordinate speed to satisfy the following merging constraints. Similar to case 1, $t_j^{h_1}$ denotes the time for speed adjustment, and $t_j^{h_2}$ represents the time for constant speed. The equations will be rewritten as follows:

$$\begin{aligned}
&s_j\left(t_j^m\right) \ge s_i\left(t_j^m\right) + h_s\left(t_j^m\right),\\
&t_j^{h_1} + t_j^{h_2} = t_j^m - t_{j-1}^m,\\
&s_j\left(t_{j-1}^m + t_j^{h_1}\right) = s_j\left(t_{j-1}^m\right) + v_j\left(t_{j-1}^m\right) \times t_j^{h_1} + a_j \times \frac{\left(t_j^{h_1}\right)^2}{2},\\
&v_j\left(t_{j-1}^m + t_j^{h_1}\right) = v_j\left(t_{j-1}^m\right) + a_j \times t_j^{h_1},\\
&0 \le v_j\left(t_j + t_j^{h_1}\right) \le v_{\max}^r,\\
&s_j\left(t_j^m\right) = s_j\left(t_{j-1}^m + t_j^{h_1}\right) + v_j\left(t_{j-1}^m + t_j^{h_1}\right) \times t_j^{h_2},\\
&s_i\left(t_j^m\right) = s_i\left(t_j + t_i^d\right) + v_i\left(t_j + t_i^d\right) \times \left(t_j^h - t_i^d\right),\\
&L_c \le s_j\left(t_j^m\right) - s_j\left(t_j\right) \le L_a + L_c,\\
&h_s\left(t_j^m\right) = v_i\left(t_j + t_i^d\right) \times t_r.
\end{aligned} \tag{23}$$

The flowchart for the merging method with cooperative velocity guidance is explained in Figure 4.

In the above algorithms, the trajectory of the preceding vehicle $j-1$ is inputted as a known data. Parameter a_j is set as a constant value d_c or a_c (comfortable acceleration) to avoid drastic variation through the whole speed adjustment time interval. Therefore, variables $t_j^{h_1}$ and $t_j^{h_2}$ are the key variables to be solved which decide the other parameters v and s. A trial method is applied to compute these variables. To this end, start by $t_j^{h_1} = 1$, and then compute $t_j^{h_2}$ to check whether the above conditions are met. If not, then set $t_j^{h_1} = 2$, and repeat these steps until finding a reliable group value $(t_j^{h_1}, t_j^{h_2})$ or the vehicle j driving out of the acceleration lane. If there is no feasible solution, the selected gap i will be deleted and turn to the next target gap.

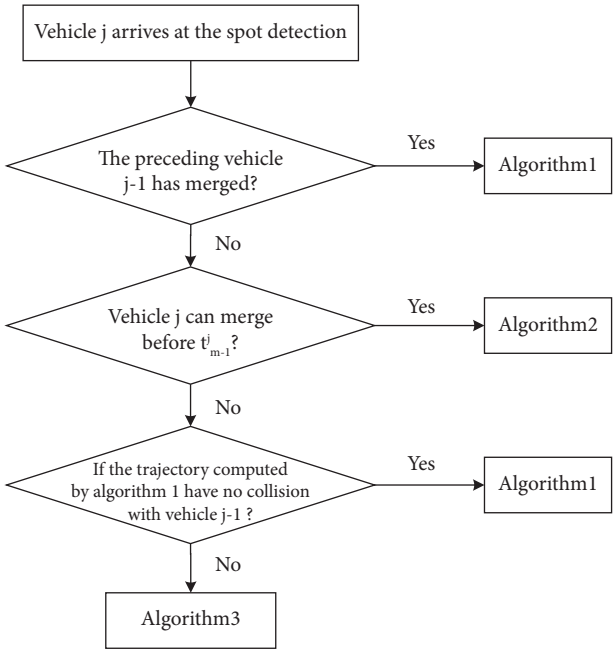

Figure 4: The flowchart of the merging method with cooperative velocity guidance.

5. Numerical Example and Results

In this section, experiments are conducted to validate the algorithm in a scene, as shown in Figure 1. The traffic flow arriving at the entrance of the research zone follows a Poisson distribution to be more realistic, and the parameters of the mean spacing time are preset as 2 s on the main road and 4 s on the ramp. All experiments are implemented and conducted within a time horizon of 120 s, which is divided into 120 intervals with each time step of $\Delta t = 1\,s$. The values of other parameters in the example are listed in Table 1.

In order to validate that the algorithm proposed in Section 2.2 can generate stable traffic flow and avoid collisions, a simulation is implemented without merging vehicles on the ramp first. The results of the velocity and position are illustrated in Figures 5 and 6, respectively. Figure 5 presents all the vehicles' trajectories along the whole time horizon. It is evident that some vehicles decelerate to guarantee a safe distance at the early steps of the simulation (displayed in Figure 5), and then accelerate to the identical speed to the preceding vehicle toreach a steady state finally. The three modes discussed in Section 2.2 all occurred in the results. In the case of sufficient gaps, the vehicles speed up to their maximum velocity without restraints. On the contrary, when the gap is small, the vehicles slow down and adjust velocity with the preceding vehicle in a near distance. Finally, a stable traffic flow with constant velocity can be formed, and the vehicle distance remains in the specific, predefined range larger than the minimum safe distance.

In Figures 5 and 6, a minor velocity variation is observed due to the safe distance at the entrance and no enroute interruption. Further, an extra example is presented to explain the vehicles' driving modes, in which the first vehicle speeds down at a comfortable deceleration during time intervals [40, 45] s. In Figures 7 and 8, a total of eight subsequent vehicles are shown to be influenced by a speed variation, but a stable state still appears after a period of time.

The programmed trajectories with merging vehicles computed by the proposed methods are shown in Figures 9 and 10. The lines printed in red and black are vehicles' trajectories on the main road and ramp, respectively.

All the cases discussed in previous sections are displayed in the results. In Figure 9, the trajectories with constant slope indicate a direct merging process without velocity variation. Some vehicles on the main road must slow down to enlarge the gap and allow ramp vehicles to enter directly, as shown by the black lines with turning points. Another phenomenon with more drastic oscillation can be observed in which the associated vehicles follow the optimized trajectories to cooperate with the other vehicles. Moreover, no vehicles can be found to stop and wait in this example, which is typical for human-driven vehicles. Correspondingly, the speeds presented in Figure 10 indicate the vehicles' velocity oscillation.

In order to verify the algorithm's effectiveness in increasing capacity and reducing travel time, further discussion and results are presented in the following figures. The test experiments are carried out with a group of different traffic volumes to reveal the influence on capacity. Also, a comparison with the human-driven vehicles is derived to verify the algorithm's advantages (the capacity is computed by the vehicles driving out of the merging zone at a specific time).

Results in Figures 11 and 12 are presented as total capacity with various entering traffic volumes. In Figure 11, it can be observed that the total capacity increases quickly with the volume on the main road in cases of low ramp flow (depicted in the left parts of the lines). It is evident that vehicles on the ramp have little impact on the main road, and vehicles' velocities has a slight variation in this situation. Otherwise, with the increase in ramp flow, the capacity presents a slower increase or decline, and reflects an irregular trend. Simultaneously, the traffic flow on the main road was heavily affected. Merging vehicles leads to drastic speed fluctuation and unsmooth trajectories. When the main road volume increases to a value of 1800 veh/h and the ramp flow is between 500 and 1000 veh/h, a capacity decline appears due to high density and accompanying congestion. Noticeably, the volume is converted into the vehicles' mean time and space in the experiments.

As illustrated in Figure 12, a distinct result can be observed that the entering-out vehicles always increase with the input flow, and the increment rate becomes gentler gradually facing with the higher flow on the ramp. This finding indicates that main road volume is a critical element in influencing capacity due to higher speed and driving priority, and that excessive ramp flow can generate congestion, velocity deceleration, and lower capacity, conversely.

The third experiment is conducted to assess the algorithm's effectiveness in improving road efficiency by comparing it with the nonoptimized cases. In the contrast example, no instruction will be issued to vehicles before arriving at the auxiliary lane, and vehicles will make

Table 1: Example parameters values.

Variables	Description	Value
L_a	Length of acceleration lane	400 m
L_c	Distance between detection point and merging spot	100 m
$v_{\max}^m$	Maximum velocity on main road	30 m/s
$v_{\max}^r$	Maximum velocity on ramp	25 m/s
$a_{\max}, a_c$	Maximum/comfortable acceleration	3 m/s^2, 2.5 m/s^2
$d_{\max}$, d_c	Maximum/comfortable deceleration	2 m/s^2, 1.5 m/s^2
L	Length of the vehicle	3 m
f_1	Rate of free acceleration of vehicles	0.4 s
f_2, f_3	Feedback gain of weight parameters	0.23 s^2, 0.07 s
f_4, f_5	Error of weight coefficient of vehicle distance	0.45 s^2, 0.25 s
t_r	Reaction time	0.6 s
L_1	The distance range in free mode	2 s∗v
L_2	The distance range in approximation mode	1 s∗v

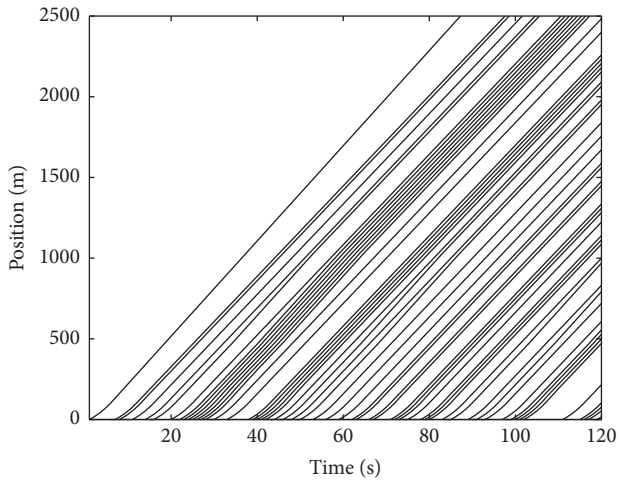

Figure 5: Trajectories without merging vehicles.

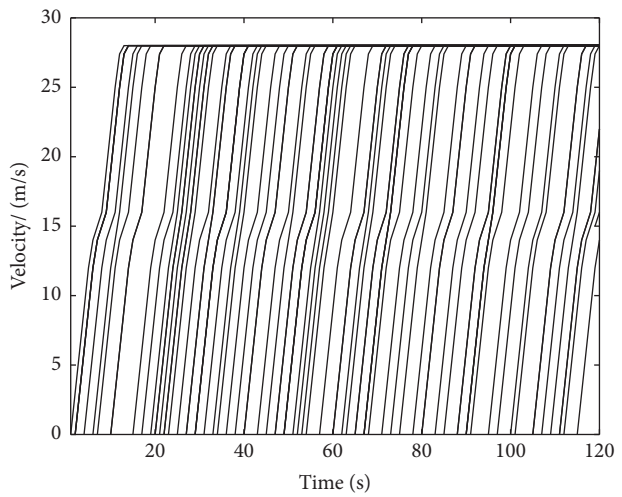

Figure 6: Velocities without merging vehicles.

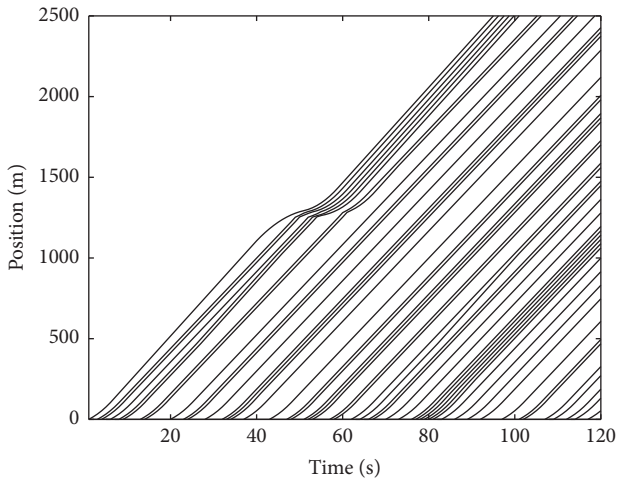

Figure 7: Trajectories with enroute disruption.

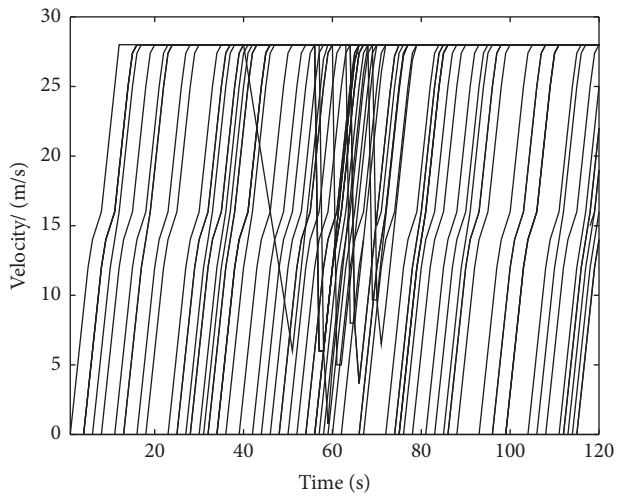

Figure 8: Velocity with enroute disruption.

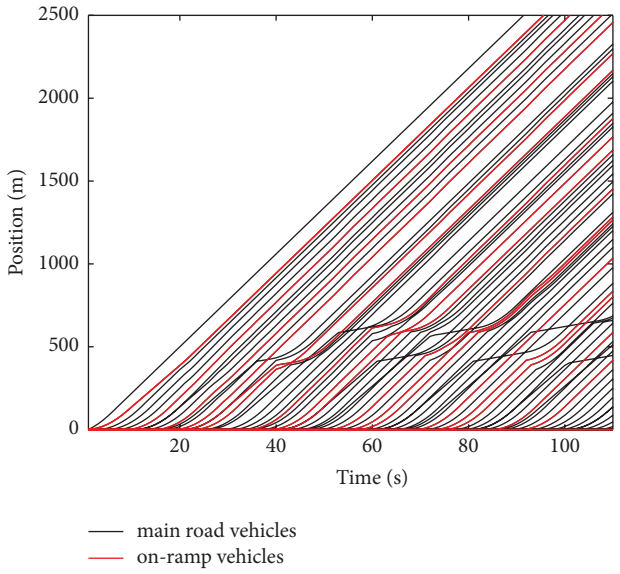

Figure 9: Trajectories with merging vehicles.

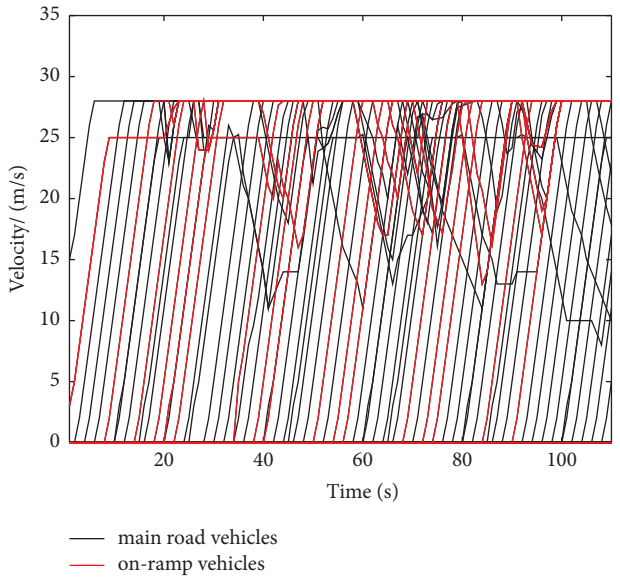

Figure 10: Velocities with merging vehicles.

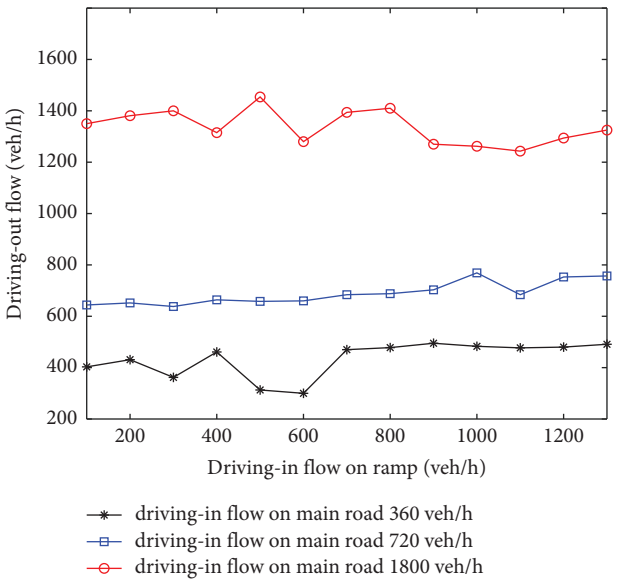

Figure 11: Influence of ramp input flow.

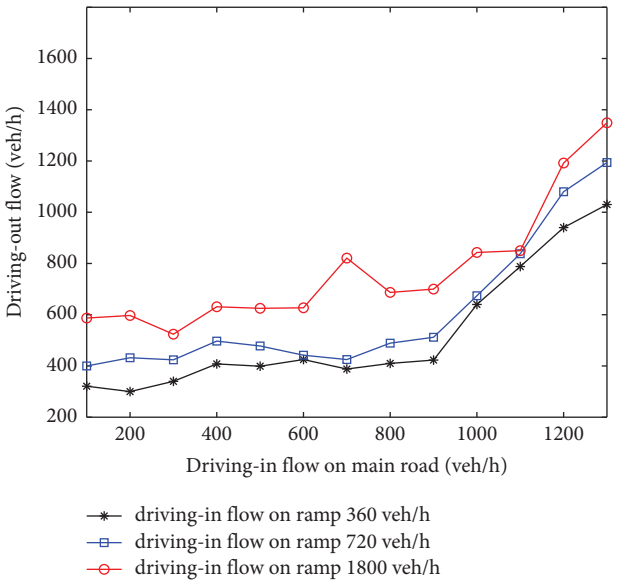

Figure 12: Influence of main road input flow.

self-decision by observing the real-time traffic state. A contrast simulation process is described as follows:

At each time t', which satisfied vehicles already driving into the auxiliary lane, we denote the preceding and subsequent vehicle as $i-$ and i on the main road.

(1) If the following constraints are simultaneously satisfied, vehicle i merges into the main road directly:

$$s_j(t') - s_i(t') \geq v_i(t') \times t_r, \tag{24}$$

$$s_{i-1}(t') - s_j(t') \geq v_j(t') \times t_r. \tag{25}$$

(2) Contrarily, adjust the speed to enlarge the gaps when $s_j(t') < L_a + 2L_c - L_{\min}$. $L_{\min}$ is the minimum length to the end which valued 10 m in the experiment.

If the distance to vehicle $i-1$ is not satisfied according to (25), vehicle j on the ramp slows down with a comfortable deceleration:

$$a_j(t') = d_c. \tag{26}$$

Otherwise, if the distance is not satisfied according to (24), vehicle i on the main road slows down:

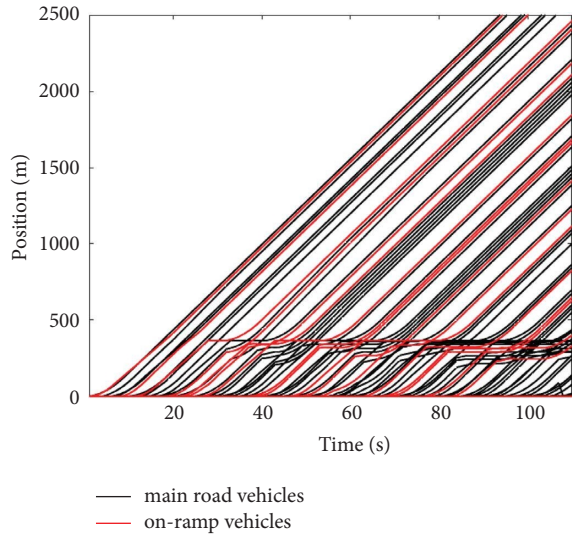

Figure 13: Vehicle trajectory line without guiding.

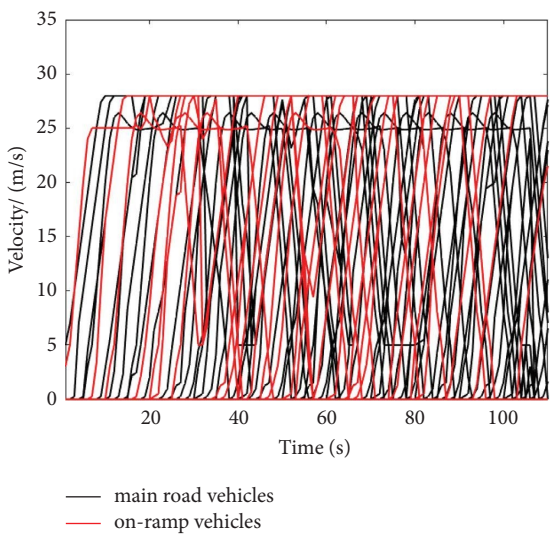

Figure 14: Vehicle speed graph without guiding.

$$a_i(t') = d_c. \tag{27}$$

If $s_j(t') > L_a + 2L_c - L_{\min}$, $a_j(t') = d_{\max}$, vehicle j slows down with the maximum deceleration and stops to wait for a sufficient gap.

This self-decision algorithm is applied to the same example discussed previously. The parameters are set to the same value to guarantee experimental consistency. The results of vehicles' trajectories and velocity variations are illustrated in Figures 13 and 14. It is evident that the velocity fluctuation seems more drastic when driving in the auxiliary lane to search for an applicable gap. Eventually, several vehicles are forced to stop, leading to more travel time costs. Compared with the results in Figures 9 and 10, the trajectories present much more unsmooth travels and the total

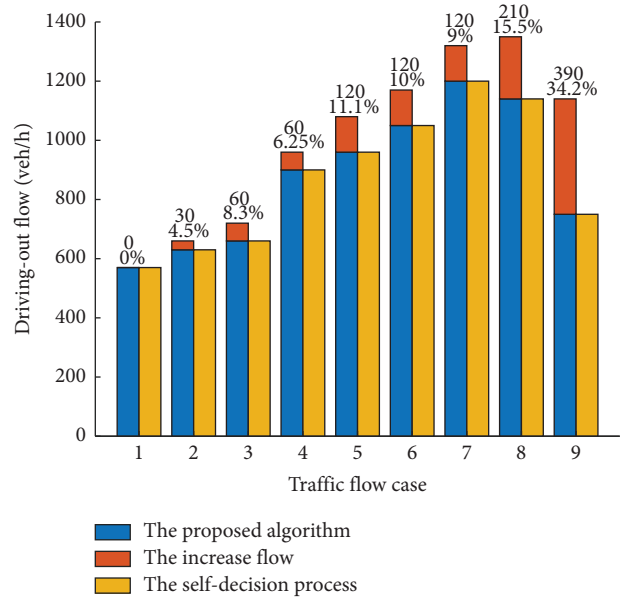

Figure 15: Comparative results with various traffic flow.

driving-out vehicles are smaller in a fixed period. These findings indicate that the proposed algorithm is capable of improving capacity as well as reducing travel time.

Figure 15 reports the comparative results of the driving-out vehicles in 120 s under various initial traffic flow values. As shown in Figure 15, the comparison results for nine groups are presented, and the driving-in flows on the main road and ramp are set as (720, 200), (720, 400), (720, 600), (1200, 200), (1200, 400), (1200, 600), (1800, 200), (1800, 400), and (1800, 600), respectively. An efficiency improvement is obvious, especially for congested states.

6. Discussions and Conclusions

This study addresses an assessment of a cooperative algorithm for merging vehicles' trajectories optimization in the connected zone with communication facilities. The main objective is to obtain smooth vehicle speeds and increase the driving-out vehicles by using V2X communication. Meanwhile, safety distance, kinematic restraints, and driving properties for ACC vehicles are considered the constraints required to be satisfied. In the proposed method, vehicles are organized one by one, complying with FIFO rules, and the preceding vehicle's scheme is stored and applied for the subsequent optimizations. For an individual vehicle, the first step is to search for gaps and decide the priorities needed to verify feasibility and compute trajectories. The next step focuses on programming trajectories for the vehicles to insert into a proper gap by cooperating with the vehicles on the main road. The proposed method has been explained with a numerical example, and the comparative experiments indicate some meaningful findings. First, the proposed method provides relatively smooth trajectories to guarantee safe distances and improve merging efficiency. Vehicles are permitted to merge into the main road before arriving at the exit of the auxiliary lane and avoid stopping and waiting. The

velocity fluctuates slightly, and only cooperative vehicles need to follow the instructions. Second, in each loop for an individual vehicle, the algorithm only needs to compute the related vehicles' trajectories by inputting other vehicles' data. Therefore, the algorithm has low computational complexity and responds rapidly to vehicles' requests. Also, the optimized scheme can be computed and issued to connected vehicles instantaneously. Therefore, the proposed method is applicable to connected traffic management on ramps in reality.

This study can be extended to deal with some unresolved issues. Firstly, if the mixed traffic flow is composed of ACC and human-driven vehicles, which will be popular for a long time, the car-following and merging behavior will be significantly influenced by the loss of information release and reception. Secondly, dealing with ACC vehicles, a primary stage of intelligent vehicles, is the objective of this work. CACC vehicles driving in a platoon or automatic vehicles relying on central control will be the further developments, and algorithms for different vehicles will be an issue that deserves attention. For example, if a vehicle inserts into a CACC platoon, it is necessary to focus on the platoon's division and reorganization. Meanwhile, platoon stability is also an insignificant objective. Similarly, the driving behavior and trajectory computation of AVs have distinctive properties. Therefore, the traffic organization in merging zones deserves to conduct further research for multiple scenarios.

Data Availability

The data 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 interest.

Acknowledgments

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