Research Article

Driver Source-Based Traffic Control Approach for Mitigating Congestion in Freeway Bottlenecks

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On-ramp control is an effective way to mitigate traffic congestion in freeways. In this study, a traffic control approach is developed based on the OD data of a regional freeway to alleviate the traffic overload in freeway bottlenecks. We first locate the major driver sources of the freeway bottlenecks and identify the on-ramps for implementing the traffic control schemes. Next, the differential evolution algorithm is employed to calculate the optimal control time at each traffic control on-ramp. The results indicate that the major driver sources of the freeway bottlenecks are limited. Traffic congestion in the freeway bottlenecks can be effectively mitigated by adaptively controlling the waiting time of vehicles at the on-ramps of their major driver sources.

1. Introduction

In the past few decades, freeway congestion has become a common traffic problem all over the world [1, 2]. Traffic congestion results in travel delays and also exacerbates road safety and environmental problems [3]. For example, the emission rate in freeway congestion is about 10–61% higher than the emission rate under free-flow traffic condition [4]. Freeway congestion often occurs near freeway bottlenecks, which are conventionally defined as the freeway segments with travel demand exceeding their capacity. The congestion at a freeway bottleneck can be mitigated by controlling the time that vehicles arrive at the freeway bottleneck. Therefore, many freeway congestion control approaches have been proposed, among which on-ramp control is a widely used traffic control approach that can effectively mitigate traffic congestion [5].

Single-point on-ramp control methods are first developed. Demand capacity control and percent occupancy control are the two original control approaches [6]. The idea of the two control strategies is straightforward: when the freeway segment occupancy is detected to exceed the pre-set threshold, the on-ramp vehicle passing rate will be adjusted to the pre-set minimum value. Papageorgiou et al. proposed an on-ramp control algorithm based on the ALINEA algorithm [7]. ALINEA is developed based on classical control theory methods, which is the first on-ramp control strategy using feedback in a systematic way. Later, based on the reinforcement learning theory of intelligence algorithm, Wang et al. proposed the reinforcement learning ramp metering (RLRM) control method for single entrance ramp under incomplete information [8]. Their simulation results indicated that the RLRM control method could achieve good control performance. The single-point on-ramp control strategy is simple, flexible, and effective and has been widely used in practice. However, single-point on-ramp control does not consider the correlation between traffic flows from different on-ramps and is only applicable to low traffic volume condition. Under heavy traffic condition, single-point on-ramp control can lead to long queues at the controlled on-ramp.

Coordinated on-ramp control represents another mainstream approach for mitigating freeway congestion. Coordinated on-ramp control can be broadly divided into cooperative control and bottleneck control. The aim of the cooperative control approach is to reduce the adjustment
rate of upstream on-ramps. For example, the heuristic ramp metering coordination (HERO) algorithm proposed by Papamichail et al. belongs to the cooperative control approach [9]. The HERO algorithm is an extended version of the ALINEA algorithm, which achieves coordinated control between multiple on-ramps. The bottleneck control approach first determines the main freeway bottlenecks and the expected reduction in traffic volume passing the bottlenecks. Next, the upstream on-ramps are controlled to restrict the passing rate of vehicles at the bottlenecks. Bottleneck control algorithms include BOTTLENECK [10], ZONE [11], and SWARM [12]. Later, Chai et al. proposed a heuristic algorithm for freeway on-ramp control to deal with the traffic congestion caused by accidents [13]. Chai and Gao employed the Greenshields model to determine the level of traffic congestion in freeways and improved the BOTTLENECK algorithm [14].

The intelligence optimization algorithm, which was originally used for solving optimal problems, has recently been applied to the area of freeway on-ramp control. Given the objective function and constraints, the intelligence optimization algorithm can solve the traffic control strategies for mitigating traffic congestion (e.g., the optimal flow rate at on-ramps). Fares and Gomaa proposed an intelligent reinforcement learning algorithm based on the Markov model for freeway congestion control, named Q-learning algorithm [15]. The algorithm balances the capacity and the demand for freeway. Belletti et al. proposed to integrate deep reinforcement learning into the control system [16] and designed a new multi-agent control algorithm without parameters. Researchers also employed a more accurate BeATS simulator and achieved a similar control effect [17]. Liang et al. proposed a compound on-ramp control system composed of a coordinated control layer and a direct control layer [18]. The authors used the particle swarm optimization algorithm to solve the coordinated control scheme of multiple on-ramps.

Although many coordinated on-ramp control approaches have been proposed, these approaches usually focused on the limited number of on-ramps near the freeway bottlenecks. However, upstream on-ramps located far away may also contribute large traffic flow to the bottlenecks. These upstream on-ramps could be the key traffic control candidates. In this study, we use the actual OD flow data between on-ramps to simulate the traffic flow in an actual regional freeway network. The major driver sources [19, 20], which contribute to the majority of the traffic flow at the freeway bottlenecks, are identified to determine the on-ramps for implementing a traffic control scheme. Next, we develop a driver-source-based traffic control approach to adjust the time that vehicles pass the controlled on-ramps. Using the differential evolution algorithm, dynamic traffic control schemes are generated for each controlled on-ramps. The core idea of the proposed approach is to postpone the arrival time of vehicles at the freeway bottlenecks and mitigate the traffic overload by increasing the waiting time of vehicles entering the controlled on-ramps. Tracing the major driver sources of freeway bottlenecks can filter out the on-ramps that are not closely related to traffic congestion, reducing the computational complexity of traffic control models. Finally, the proposed approach can solve the traffic control scheme in actual large-scale regional freeway networks, which is different from previous approaches that usually focused on small-scale networks.

2. Data

2.1. Freeway Network Data. This study uses the freeway network data of Hunan Province, which was provided by Hunan Communications Research Institute Co., Ltd. The data recorded the detailed information of 450 toll stations and 12,687 freeway segments. Each toll station corresponds to an on-ramp where a traffic control scheme can be potentially implemented. The name, ID, longitude, and latitude of each toll station were recorded in the data. The attributes of each freeway segment, which include the length, latitude and longitude of the start point and endpoint, number of lanes, and direction, were also recorded.

2.2. Freeway OD Data. The OD data of the studied regional freeway were provided by Hunan Communications Research Institute Co., Ltd. We use the OD data collected during a period from May 13, 2019, to May 19, 2019. The origin and destination of each trip in the OD data are toll stations (on-ramps). The OD data recorded the number of trips between each pair of toll stations (on-ramps) during each one-hour time period. Roughly 1,454,400 trips were recorded during the one-week data observational period.

3. Modelling Framework

In this study, we propose a model for generating the multi-ramp control scheme for mitigating traffic congestion at freeway bottlenecks. The proposed model belongs to integer programming models [21], which were often used in public transportation management [22, 23]. In Section 3.1, we establish a traffic simulation method to simulate the vehicle movements from on-ramps to freeway bottlenecks. In Section 3.2, we introduce the method for identifying the on-ramps for implementing traffic control schemes. In Section 3.3, we develop the driver-source-based traffic control model by solving the multi-ramp control scheme using the differential evolution algorithm.

3.1. Traffic Simulation. The incremental traffic assignment method is characterized by the good features of simple, feasible, and adjustable precision and is often used in practice. Therefore, the incremental assignment method is employed in this study, in which the road resistance function is the Bureau of Public Road (BRP) function:

\[ t = t_0 \left(1 + \alpha \left(\frac{Q}{C}\right)^\beta\right), \]

where \( t \) represents the time required to pass a freeway segment, \( t_0 \) represents the free travel time of the freeway segment, \( Q \) represents the traffic volume, and \( C \) represents the capacity of the freeway segment. The default values \( \alpha = 0.15 \) and \( \beta = 4 \) are used. Traffic volume assigned at each time,
The traffic simulation method includes the following four steps:

1. The departure time for each vehicle $c$ departs in time window $t$ is randomly generated. The departure time $t_D(c,r,t)$ follows a uniform distribution during $t$ [24, 25]:

$$t_D(c,r,t) \in t, \quad F(t_D(c,r,t)) = \frac{1}{t}, \quad r \in \Omega_r, c \in \Omega_c, t \in \Omega_t,$$

where $F(t_D(c,r,t))$ is the probability density function of $t_D(c,r,t)$.

2. Previous studies indicated that vehicle speeds follow normal distributions in freeways [26–28]. Here, we set the mean of vehicle speed to 88.671 km/h and the standard deviation of vehicle speed to 13.744 km/h [29]. We assume that vehicle speeds follow a normal distribution, and a speed value is randomly generated based on the following equation for each vehicle every 2 minutes:

$$v_{m\Delta t}(c) \sim N(88.671, 13.744^2), \quad \Delta t = 2\min.$$  

3. The location of a vehicle is calculated according to the assigned path. The time that a vehicle arrives at the freeway bottleneck is calculated using the following equation:

$$\int_0^{t_{\text{trip}}(c,r)} v_{m\Delta t}(c) \, dt = L(r), \quad r \in \Omega_r, c \in \Omega_c.$$  

The time that a vehicle arrives at the freeway bottleneck equals the departure time plus the travel time of the vehicle:

$$t_A(c) = t_D(c,r,t) + t_{\text{trip}}(c,r), \quad r \in \Omega_r, c \in \Omega_c, t \in \Omega_t,$$

When traffic control scheme is implemented, the time that a vehicle arrives at the freeway bottleneck equals the departure time plus the travel time and the additional waiting time for entering the controlled on-ramp:

$$t_{A\text{control}}(c) = t_D(c,r,t) + t_{\text{trip}}(c,r) + t_w(r,t), \quad r \in \Omega_r, c \in \Omega_c, t \in \Omega_t.$$  

4. When there is no traffic control, the traffic flow $f(i)$ of the freeway bottleneck is calculated based on the time $t_A(c)$ when each vehicle arrives at the bottleneck:

$$f(i) = \sum_{c \in \Omega_c, r \in \Omega_r} p(c,i) p(c,i) = \begin{cases} 1, & t_A(c) \in i, \\ 0, & t_A(c) \notin i. \end{cases}$$

When traffic control is implemented, the traffic flow $f_{\text{control}}(i)$ of the freeway bottleneck is calculated based on the time $t_{A\text{control}}(c)$ when each vehicle arrives at the bottleneck:

$$f_{\text{control}}(i) = \sum_{c \in \Omega_c, r \in \Omega_r} p(c,i) p(c,i) = \begin{cases} 1, & t_{A\text{control}}(c) \in i, \\ 0, & t_{A\text{control}}(c) \notin i. \end{cases}$$

3.2 Identifying the On-Ramps for Implementing Traffic Control Scheme. As shown in (9), we define 80% of the maximum traffic flow of a freeway bottleneck as the upper bound of its ordinary traffic flow $f_b$ [30]. The time period when the traffic flow is larger than $f_b$ is defined as the heavy traffic period. Traffic control starts 15 minutes earlier than the start of the heavy traffic period and ends 15 minutes later than the end of the heavy traffic period. To prevent serious traffic congestion at freeway bottlenecks, the upstream on-ramps are selected as the candidate traffic control on-ramps.

$$f_b = \text{Max}\{f(i)\} \times 0.8, \quad i \in \Omega_i.$$

We define the driver source of a freeway segment as the on-ramp that contributes to the traffic flow of the freeway segment. As shown in Figure 1, the on-ramps contributing to the traffic flow of the freeway segment are denoted as their driver sources (see the red dots in Figure 1). That is, vehicles entering these on-ramps contribute to the traffic flow of the freeway segment. There are also some on-ramps, which do not contribute to the traffic flow of the bottleneck freeway segment (see the grey dots in Figure 1). The freeway segments that drivers use to travel from the driver sources to the bottleneck freeway segment are highlighted in blue. Next, we define a freeway segment’s major driver sources (MDS) as the top ranked driver sources that contribute 80% of its traffic flow [19]. We select the on-ramps acting as the MDS of the freeway bottleneck as the traffic control on-ramps. The traffic control duration of each controlled on-ramp is affected by its distance from the freeway bottleneck. The control period is relatively short for on-ramps far away from the bottleneck, whereas the control period is relatively long for the on-ramps in the vicinity of the bottleneck.

3.3 Generating Traffic Control Scheme Using Differential Evolution Algorithm. Differential evolution (DE) is a powerful evolutionary algorithm for solving optimization problems [31], and it has been successfully applied in traffic signal control [32, 33]. The studied multi-ramp vehicle waiting time control problem belongs to the combinational
optimization problem and shares similar properties with the traffic signal control problem. Therefore, we use the differential evolution algorithm to generate the dynamic traffic control scheme.

In the differential evolution algorithm, a traffic control scheme is expressed as a decision vector \( X = (x_1^1, x_1^2, \ldots, x_r^j, \ldots, x_n^j) \), where \( n \) is the number of controlled on-ramps, \( t \) is the number of time windows implementing the traffic control scheme, and \( x_r^j \) represents the extra time that a vehicle needs to wait when passing a controlled on-ramp \( r \) during time window \( j \). In each generation, a traffic control scheme is used to obtain the traffic simulation results (Figure 2). When a vehicle arrives at a traffic control on-ramp \( r \), the vehicle stops for an extra time \( t_w(r) \) and the arrival time of the vehicle is postponed at the freeway bottleneck, therefore reducing the maximum traffic flow at the bottleneck. A flowchart describing the traffic simulation process and the traffic scheme solution process is shown in Figure 2.

The objective of the proposed traffic control approach is to avoid traffic overload at bottleneck segments by postponing the arrival time of some vehicles. In other words, we try to smooth the traffic flow fluctuations to avoid traffic.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>( m )</td>
<td>Moment</td>
</tr>
<tr>
<td>( t )</td>
<td>Index of traffic control time windows</td>
</tr>
<tr>
<td>( i )</td>
<td>Index of traffic statistic time windows</td>
</tr>
<tr>
<td>( r )</td>
<td>Index of on-ramps</td>
</tr>
<tr>
<td>( c )</td>
<td>Index of vehicles arriving at the freeway bottleneck</td>
</tr>
<tr>
<td>( t_j )</td>
<td>The time span of a time window</td>
</tr>
<tr>
<td>( \Omega )</td>
<td>Set of time windows for implementing a traffic control scheme</td>
</tr>
<tr>
<td>( \Omega_i )</td>
<td>Set of time windows for traffic statistics</td>
</tr>
<tr>
<td>( \Omega_r )</td>
<td>Set of on-ramps for implementing a traffic control scheme</td>
</tr>
<tr>
<td>( \Omega_c )</td>
<td>Set of vehicles from on-ramp ( r ) to the freeway bottleneck</td>
</tr>
<tr>
<td>( L(r) )</td>
<td>The distance from on-ramp ( r ) to the freeway bottleneck</td>
</tr>
<tr>
<td>( v_{	ext{max}}(c) )</td>
<td>The speed of vehicle ( c ) from time ( m ) to ( m + \Delta t )</td>
</tr>
<tr>
<td>( t_D(c,r,t) )</td>
<td>The time when vehicle ( c ) arrives at on-ramp ( r ) in time window ( t )</td>
</tr>
<tr>
<td>( t_{	ext{trip}}(c,r) )</td>
<td>Travel time of vehicle ( c ) from on-ramp ( r ) to the freeway bottleneck</td>
</tr>
<tr>
<td>( t_A(c) )</td>
<td>The time when vehicle ( c ) arrives at the freeway bottleneck without traffic control</td>
</tr>
<tr>
<td>( t_{A,\text{control}}(c) )</td>
<td>The time when vehicle ( c ) arrives at the freeway bottleneck under traffic control</td>
</tr>
<tr>
<td>( t_w(r,t) )</td>
<td>The extra waiting time of vehicles entering on-ramp ( r ) in time window ( t )</td>
</tr>
<tr>
<td>( p(c,i) )</td>
<td>A binary variable determines whether vehicle ( c ) arrives at the freeway bottleneck in time period ( i ) (if ( p(c,i) = 1 ), vehicle ( c ) arrives at the freeway bottleneck in time period ( i ); otherwise, vehicle ( c ) arrives at the freeway bottleneck during another time period)</td>
</tr>
<tr>
<td>( f(i) )</td>
<td>The traffic flow of the freeway bottleneck in time period ( i ) without traffic control</td>
</tr>
<tr>
<td>( f_{\text{control}}(i) )</td>
<td>The traffic flow of the freeway bottleneck in time period ( i ) under traffic control</td>
</tr>
</tbody>
</table>

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**Figure 1:** Illustration of the driver sources of a bottleneck freeway segment. The red dots denote the on-ramps that contribute to the traffic flow of the bottleneck freeway segment, which are defined as the driver sources in this study. The on-ramps that do not contribute to the traffic flow of the bottleneck freeway segment are denoted by the grey nodes. The freeway segments that drivers use to travel from the driver sources to the bottleneck freeway segment are highlighted in blue.

**Figure 2:** Flowchart of the traffic simulation process and traffic scheme solution process.
overload at the freeway bottleneck. Therefore, the objective function is defined as follows:

\[
F = \sum_{f_{\text{control}}(i) > f_b} \lambda(f_{\text{control}}(i) - f_b)^2 + \sum_{f_{\text{control}}(i) \leq f_b} (1 - \lambda)(f_b - f_{\text{control}}(i))^2,
\]

(10)

where \( F \) represents the fluctuation of traffic flow after implementing the traffic control scheme, \( f_{\text{control}}(i) \) is the traffic flow of the freeway bottleneck in time window \( i \), and \( \lambda \) is the penalty coefficient, which is set to 0.8 to put more weight on the traffic flow exceeding \( f_b \). Using the objective function, the optimized traffic control scheme can be obtained. The detailed methods are as follows:

Step 0 (initial population): the initial population is randomly generated. The number of populations \( N_p \) and the maximum number of iterations \( N_g \) are set. \( n_g = 1 \) is set. The crossover rate \( p_{CR} \) and the mutation factor \( p_F \) are set.

Step 1 (mutation): for each target vector \( X_i = (x_i(1), x_i(2), \ldots, x_i(d)) \), a new mutant vector is created using the formula \( \tilde{V}_d(x_i(1), \ldots, x_i(d)) = X_{i1} + p_F(h_{\text{ub}} - X_{i2} - X_{i3}), \) where \( X_{i1}, X_{i2}, \) and \( X_{i3} \) are randomly selected and different from each other in the population and different from \( X_i \).

Step 2 (crossover): a uniformly distributed random number \( \tau \) is set between \([0, 1] \) for each pair of \( x_i(d) \) and \( \tilde{v}_i(d) \). If \( \tau < p_{CR} \), \( u_i(d) = \tilde{v}_i(d) \), otherwise \( u_i(d) = x_i(d) \). Then, the trial vector \( U_i = (u_i(1), u_i(2), \ldots, u_i(d)) \) is generated.

Step 3: simulating trips based on each target vector and each trial vector, the objective function values of each trial vector \( U_i \) and the corresponding target vector \( X_i \) is calculated using (10).

Step 4 (selection): if the objective function value of \( U_i \) is lower than that of \( X_i, U_i \) is set to the new generation of target vector \( X_i \) to generate a new population; otherwise, vector \( X_i \) is retained.

Step 5 (stop test): if \( n_g = N_g \), the algorithm is stopped. The vector with the lowest objective function value is the best population member, and its corresponding traffic control scheme is used; otherwise, \( n_g = n_g + 1 \) is set and Step 1 is proceeded.

4. Results

In this study, two freeway segments are used as case studies. One freeway segment (freeway bottleneck A) is on Beijing-Hong Kong-Macao Expressway (Figure 3(a)). According to the reports and the news on RedNet (a news portal of Hunan), the Changsha section of Beijing-Hong Kong-Macao Expressway is often heavily congested due to large traffic flow. The other freeway segment (freeway bottleneck B), which is also often heavily congested, is on Changsha-Zhangjiajie Expressway (Figure 3(b)). The two freeway bottlenecks are used as case studies to test the proposed driver-source-based traffic control approach.

4.1. Traffic Flow Analysis. Traffic flow \( f \) passing through each freeway bottleneck is calculated every 5 minutes from 6:00 a.m. to 6:00 p.m. As shown in Figure 3, there is one traffic flow peak between 1:00 p.m. and 5:00 p.m. for bottleneck A, and there are two traffic flow peaks for bottleneck B, which are from 8:00 a.m. to 11:00 a.m. and from 2:00 p.m. to 3:00 p.m. Next, the upper bound of ordinary traffic flow \( f_b \) is calculated for each freeway bottleneck (118 vehicles/5 minutes for bottleneck A and 278 vehicles/5 minutes for bottleneck B). We find that the traffic flow at bottleneck A increases rapidly from 1:00 p.m., and the heavy traffic period (\( f > f_b \)) lasts for about 4 hours (Figure 4(a)), whereas the traffic flow at bottleneck B increases rapidly at about 8:00 a.m. and 1:45 p.m., and the heavy traffic period lasts for about 3 hours and 1 hour, respectively (Figure 4(b)). Consequently, the traffic control periods are determined for bottleneck A (1:15 p.m. to 5:25 p.m.) and bottleneck B (7:55 a.m. to 11:10 a.m. and 1:50 p.m. to 3:10 p.m.).

4.2. Identifying the On-Ramps for Implementing Traffic Control Scheme. For freeway bottleneck A, we identify a total of 123 driver sources, which include the 24 widely distributed major driver sources (MDS). For freeway bottleneck B, we identify a total of 63 driver sources, which include only one on-ramp acting as the major driver source (i.e., Changshaxi Station). The identified on-ramp contributes more than 80% of the traffic flow to bottleneck B, implying that traffic congestion at bottleneck B is mainly generated by local vehicles. We select the on-ramps acting as MDS to implement the traffic control scheme. Figure 3 shows the distribution of traffic control on-ramps, where \( C_p \) represents the traffic flow from these on-ramps to the freeway bottlenecks.

4.3. Generating the Traffic Control Scheme. The traffic control scheme, which is adjusted every 15 minutes during the traffic control period, is generated using the differential evolution algorithm introduced above. In particular, the crossover rate and the mutation factor are set to \( p_{CR} = 0.9 \) and \( p_F = 0.1 \), respectively [34], and the range of a gene \( g' \) is set to 0–120 seconds considering the tolerance of drivers. The target traffic flow volume is set to \( f_b = 94.4 \) vehicles/5 minutes for bottleneck A and \( f_b = 224.8 \) vehicles/5 minutes for bottleneck B. We generate the traffic control scheme for each controlled on-ramp using the settings above, and for each on-ramp, the traffic control time \( t \) representing the extra waiting time of vehicles at the on-ramp is solved.

Figures 5(a)–5(d) show the traffic control schemes during each 15 minutes time window from 1:15 p.m. to 2:15 p.m. Figures 5(e)–5(f) show the traffic control schemes of two controlled on-ramps (i.e., Zhuzhouqong and Changshaxi). The generated traffic control schemes adapt to freeway traffic flow and change dynamically with time. The on-ramps with the longest traffic control time during each
control period are shown in Table 2, of which Zhuzhouxi and Majiahe exhibit the highest frequency. Possible reasons could be that Zhuzhouxi and Majiahe contribute large traffic flow to the freeway bottleneck. In addition, the two toll stations are located close to the freeway bottleneck. We also calculate the total control time $T_r$ of each on-ramp during the traffic control period. We find that the on-ramps located far away from the freeway bottleneck are usually characterized by shorter traffic control time (Figure 6(a)). This finding is consistent with our practical experience on freeway congestion alleviation (e.g., the on-ramps near the bottleneck will be more strictly controlled).

4.4. Evaluating the Generated Traffic Control Scheme. For a bottleneck freeway segment, if the traffic flow in a specific time window is greater than those observed in its two adjacent time windows, a local maximum traffic flow is defined. To evaluate the generated traffic control scheme, we define the optimization performance $f_e$ as the average decrease in traffic flow after implementing a traffic control scheme:

$$f_e = \frac{\sum_{f > f_{\text{control}}}(f - f_{\text{control}})/f}{n_d},$$

where $f$ represents the original local maximum traffic flow of the freeway bottleneck, $f_{\text{control}}$ represents the traffic flow of the freeway bottleneck after implementing a traffic control scheme, and $n_d$ represents the number of local maxima of traffic flow.

We find that the maximum traffic flow $f_{\text{max}}$ decreases by 14.41% for bottleneck A and 4.68% for bottleneck B after implementing the traffic control scheme. The optimization performance $f_e$ is 7.19% for bottleneck A and 4.31% for bottleneck B. Hence, the proposed driver-source-based traffic control approach is more effective for mitigating traffic congestion at freeway bottlenecks with more major driver sources. An explanation is that bottleneck B only has a single MDS, and the generated traffic control scheme is similar to single-point on-ramp control, which has a limited congestion mitigation effect. While for bottleneck A, the traffic flow is contributed by several upstream MDS, the corresponding traffic control schemes are more flexible, which could be the reason for the stable traffic flow control results shown in Figure 7(a).

Implementing the traffic control scheme will increase the travel time of some drivers. We analyze the delay time $t_d$ of the trips passing through the freeway bottlenecks. The average trip delay time is only 0.833 minute for bottleneck A and 0.715 minute for bottleneck B, which we believe are within the tolerance of drivers. Given that traffic control is implemented on all vehicles entering the controlled on-ramps, trip delay will also be induced by the vehicles not heading to the freeway bottlenecks. However, we find that the average trip delay of these vehicles is 0.771 minute for bottleneck A and 0.722 minute for bottleneck B, which we believe are also within the tolerance of drivers. Hence, while a small number of vehicles are slightly postponed, the proposed traffic control approach can effectively reduce the large traffic flow at the freeway bottlenecks.

Implementing traffic control schemes could also lead to queues of vehicles at controlled on-ramps. At metered on-ramps, the arrival rate represents the on-ramp demand, whereas the departure rate represents the metering rate. Consequently, the queue length is the accumulated difference between the arrival rate and the departure rate over time [35]. We assume that vehicles can access an on-ramp directly when the traffic control scheme is not implemented. When the traffic control scheme is implemented, vehicles have to wait, and a queue is formed. We calculate the queue length for all controlled on-ramps. The average maximum queue length of these on-ramps is about 16 vehicles. Daoren and Xiaotang are the two on-ramps that contributed the most traffic flow volume to the bottleneck of Beijing-Hong Kong-Macao Expressway. The daily average number of vehicles arriving at Daoren was 9,726 vehicles/day, and the daily average number of vehicles arriving at Xiaotang was
10,190 vehicles/day. Figure 8 shows that the maximum number of vehicles in the queue is 24 at Daoren and 19 at Xiaotang when the proposed traffic control scheme is implemented. Therefore, the traffic control method proposed in this study will not cause excessive queues at controlled on-ramps, which further validates the practicability of the proposed method.

4.5. Comparison with On-Ramp Control Approach without Tracing Driver Sources. In general, there are many upstream on-ramps for a bottleneck freeway segment, and the congestion mitigation effect is determined by the selection of on-ramps for traffic control. Previous on-ramp control approaches usually selected the upstream on-ramps in the vicinity of the bottleneck freeway segment [3, 18]. However, in this study, the on-ramps are selected based on a comprehensive analysis of the driver sources. Therefore, the key on-ramps contributing a considerable volume of traffic flow to the congested segment can be identified to achieve a better congestion mitigation effect. To show the advantage of the proposed on-ramp control method based on driver source information, we compare it with previous methods that
control the traffic flow of upstream on-ramps near the bottleneck segment. Given that bottleneck B has only one major driver source, which is the nearest on-ramp to bottleneck B, there is no difference between the two traffic control approaches. Taking bottleneck A as an example, 24 major driver sources of the freeway bottleneck and 24 upstream on-ramps near the bottleneck are, respectively, selected for traffic control (Figure 9). Using the differential evolution algorithm, traffic control schemes are generated for each controlled on-ramp using the proposed method and previous control strategy.

We find that when the upstream on-ramps near the freeway bottleneck are selected for traffic control, the maximum traffic flow $f_{\text{max}}$ of the bottleneck decreases by 8.47% (Table 3). However, when the major driver sources of the bottleneck are selected for traffic control, the maximum traffic flow $f_{\text{max}}$ of the bottleneck decreases by 14.41% (Table 3). That is, the proposed driver-source-based method can achieve a 70% more reduction in $f_{\text{max}}$ than the previous control strategy. We also find that when the upstream on-ramps near the freeway bottleneck are selected for traffic control, the optimization performance $f_{\epsilon}$ is only

Figure 5: (a)-(d) Geographical distribution of controlled on-ramps during different time windows for Beijing-Hong Kong-Macao Expressway. Colour and size of each circle indicate the traffic control time $t_c$ of each on-ramp. (e)-(f) Time-varying traffic control time $t_c$ of a controlled on-ramp of (e) Beijing-Hong Kong-Macao Expressway and a controlled on-ramp of (f) Changsha-Zhangjiajie Expressway.
71.6% of that achieved by implementing the driver-source-based control strategy. In summary, selecting the major driver sources of freeway bottleneck for traffic control can achieve a better congestion mitigation effect. An explanation is that a large number of vehicles arriving at the freeway bottleneck may come from the on-ramps several hundred kilometers away. Controlling on-ramps near the freeway bottleneck could not affect the arrival of this group of vehicles.

5. Discussion

Due to the lack of actual traffic state data, we could not validate the simulated traffic states directly. However, the methods that we employed to model the traffic states have theoretical and experimental basis. In this section, we elaborate the basis of the hypotheses used in the simulation model.

In the proposed simulation method, we assume that vehicles arrive at an on-ramp evenly in time, which is a widely used assumption in previous studies. For example, Yang et al. studied the mechanism of traffic flow in the on-ramp junction areas and assumed that vehicles arrive at an on-ramp evenly in time [24]; Yang et al. proposed a method to measure the queue length at an on-ramp and assumed that vehicles arrive at the on-ramp evenly in time when building the micro-simulation model [25].

For the simulation of vehicle movement, we assume that vehicle speed follows a normal distribution given that many studies have discovered that vehicle speeds in freeways follow normal distributions. For example, Yan et al. analyzed the distributions of vehicle speeds at different sections of freeways in different areas. The authors found that vehicle speeds in freeways follow normal distributions [29]; Zhou et al. collected the traffic speed data at several freeway

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**Table 2: The on-ramps with the longest traffic control time for mitigating traffic congestion of the freeway bottleneck in Beijing-Hong Kong-Macao Expressway.**

<table>
<thead>
<tr>
<th>Time period</th>
<th>Location</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>Daoren</td>
</tr>
<tr>
<td>2</td>
<td>Daoren</td>
</tr>
<tr>
<td>3</td>
<td>Lilingdong</td>
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<tr>
<td>4</td>
<td>Zhuting</td>
</tr>
<tr>
<td>5</td>
<td>Zhuzhouxi</td>
</tr>
<tr>
<td>6</td>
<td>Youxiandong, Liling Industrial Park</td>
</tr>
<tr>
<td>7</td>
<td>Sanpu</td>
</tr>
<tr>
<td>8</td>
<td>Zhuting</td>
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<tr>
<td>9</td>
<td>Majiahe</td>
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<tr>
<td>10</td>
<td>Majiahe</td>
</tr>
<tr>
<td>11</td>
<td>Zhuzhouxi</td>
</tr>
<tr>
<td>12</td>
<td>Zhuzhouxi, Zhuzhoubei</td>
</tr>
<tr>
<td>13</td>
<td>Yuetang</td>
</tr>
<tr>
<td>14</td>
<td>Xiangtang</td>
</tr>
<tr>
<td>15</td>
<td>Zhuzhoudong</td>
</tr>
<tr>
<td>16</td>
<td>Zhuzhoubei</td>
</tr>
<tr>
<td>17</td>
<td>Majiahe</td>
</tr>
</tbody>
</table>

**Figure 6:** Colour and size of each circle indicate the total traffic control time of each controlled on-ramp during the traffic control period. (a) For Beijing-Hong Kong-Macao Expressway. (b) For Changsha-Zhangjiajie Expressway.
sections using a laser velocimeter. The authors found that the traffic speed at the freeway section was normally distributed [26]; Zhu and Shi collected vehicle speed data of an urban expressway section and found that vehicle speeds could be fitted with a normal distribution [27]; and Tang et al. analyzed the variation of vehicle speeds using vehicle GPS data and found that the distribution of vehicle speeds in curved sections of freeways exhibited normal distribution characteristics [28].

We also tested our simulation method by analyzing the distribution of path travel time. Previous studies found that the vehicle path travel time follows lognormal distributions [36–38]. Here, the K-S test is used to test whether the simulated vehicle path travel time also follows a lognormal distribution. Two hypotheses are proposed, i.e., the null hypothesis $H_0$: vehicle path travel time conforms to the lognormal distribution and the alternative hypothesis $H_1$: vehicle path travel time does not conform to the lognormal distribution.

![Graphs of traffic flow optimization](image-url)

**Figure 7:** (a), (b) Optimization of traffic flow for freeway bottlenecks of Beijing–Hong Kong–Macao Expressway and Changzhou–Zhangjiajie Expressway. The bar chart indicates the reduction in traffic flow after implementing the traffic control scheme. The dashed black line represents the target traffic flow volume $f_{g,t}$, whereas the blue solid line represents the traffic flow under traffic control.
distribution. Next, the $p$ value is calculated to determine the result of hypothesis testing. With a given significance level $\alpha$, the null hypothesis $H_0$ is accepted at the significance level $\alpha$ if $p > \alpha$; otherwise, the null hypothesis $H_0$ is rejected at the significance level $\alpha$ if $p \leq \alpha$. Our results show that the $p$ values of the distributions of vehicle path travel time from all on-ramps to the bottleneck segment are greater than 0.05. Therefore, the null hypothesis $H_0$ is accepted; i.e., vehicle path travel time conforms to the lognormal distribution.

Based on the analysis above, we conclude that the methods that we used to model the traffic states have a theoretical and experimental basis. When more data (such as vehicle trajectory data) become available in the future, the proposed method can be further validated and improved. The main contribution of this study lies in the incorporation of driver source information in ramp metering, which could improve the performance of congestion mitigation in freeways.
6. Conclusions

In this study, we develop a driver-source-based traffic control approach for mitigating traffic congestion at freeway bottlenecks. Actual OD flow data are used to simulate vehicles’ movements in the studied regional freeway. The sources of vehicles passing through the freeway bottlenecks are located to identify the on-ramps for implementing a traffic control scheme, which is solved using the differential evolution algorithm. The traffic control approach is tested on two case study freeway bottlenecks in Hunan Province, China. The proposed approach can generate a variety of traffic control schemes for different traffic conditions. In practice, a suitable traffic control scheme can be implemented according to real-time traffic conditions.

The generated traffic control schemes are dynamic in terms of space and time. In the future, when freeway data collection facilities are upgraded, data fusion techniques [39, 40] can be incorporated into the present modelling framework for involving more data sources (e.g., vehicle trajectory data). The multisource traffic data can better reflect the traffic condition of freeway, which contributes to the traffic control with the proposed approach. Finally, the adjustment interval of traffic control scheme will affect the time flexibility of the traffic control scheme and the control effect. Therefore, the adjustment interval of the traffic control scheme can be further studied for better practical use.

Data Availability

The freeway OD data and network data used to support the findings of this study have not been made available because of the confidentiality agreement.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

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