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Research Article

Route Guidance Model with Limited Overlap on Freeway Network under Traffic Incidents

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With the increasing density of the freeway network, frequent traffic incidents on road segments have a significant impact on the operational efficiency of the road network. Therefore, it has become urgent and important to study traffic route guidance strategy on the road network level. The previous traffic route guidance method primarily focused on the congestion on the road segments where incidents occurred, with insufficient attention given to the impact of congestion on the road network level. In this study, a route guidance model with limited overlap is proposed to improve freeway network reliability under traffic incidents. Specifically, in order to explore alternative paths, we conducted a study on the problem of finding k-short paths with limited overlap. The objective is to identify a set of k-paths that are both sufficiently dissimilar and as short as possible. Then, we promptly update the route guidance information using a stochastic dynamic traffic assignment model that aligns with travelers' path choice psychology. Moreover, we use the reliability of the road network to evaluate the network performance. To illustrate the model, the Jinan freeway network is selected as an experimental study. The effectiveness of this method was validated through SUMO simulations, comparing it with alternative route guidance methods, including Yen's algorithm, A^* algorithm, and ant colony algorithm. These results show that the proposed method has proven effective in mitigating traffic congestion arising from incidents and performs well in regard to the reliability of the road network under the impact of incidents.

1. Introduction

Freeway network plays an important role in establishing connectivity among cities. They are recognized for remarkable speed and capacity in accommodating both passengers and freight [1]. When incidents occur on freeways, it may lead to a decrease in road capacity or an abnormal increase in traffic demand, which may ultimately result in significant disruptions to traffic flow. After a traffic incident occurs, one or multiple lanes are usually closed, creating a bottleneck on the road. If the traffic volume continues to increase upstream and exceeds the capacity at the bottleneck, vehicles will gradually queue up from the incident location and the queue will continue to extend upstream. If congestion is not handled promptly, vehicle queues may spread into the upstream ramp area, significantly increasing the likelihood of road network congestion. In this situation, vehicles are required to change lanes upstream of the incident. However, this may also lead to traffic disruptions and a further reduction in capacity, making it more prone to traffic incidents and causing new congestion [2].

Researchers have conducted numerous studies on traffic control strategies to improve the safety performance of transportation networks [3], which encompasses enhancing safety, traffic flow, travel time reduction, improving travel time reliability, and emission reduction. Commonly applied strategies for freeway control comprise ramp control [4, 5], mainstream control [6, 7], and route guidance [8, 9]. The route guidance involves providing drivers with optimal route options considering real-time traffic conditions. This process involves calculations and optimizations to recommend information regarding alternative routes (such as congestion, incidents, and work zones) to travelers. The objective is to achieve a balanced road network and reduce travel time for drivers [10].

The goal of traffic guidance is to find guiding strategies for finding the optimal route to reduce traffic congestion and improve the efficiency of the transportation network. The total travel time of drivers in the traffic network and the total volume of vehicles passing through the road network are commonly used evaluation indicators for route guidance strategies [11, 12]. Cui et al. [13] compared the impact of six route guidance strategies on carbon emissions. The final evaluation indicator chosen by the researchers was the total unit emission, and they assessed the effect of various guidance strategies on travel time. The findings indicated that route guidance leads to a reduction in vehicle traffic emissions.

In recent years, with the development of the network theory, there have been increasing studies examining the impact of traffic control methods on road networks [12]. Numerous studies have been conducted to evaluate the effectiveness of freeway traffic control measures in terms of road network performance. Therefore, there is considerable value in examining the performance of freeway networks under the influence of incidents. Wen et al. [14] introduced a hierarchical SARSA learning-based route guidance algorithm for efficiently guiding vehicles in large-scale road networks. They proposed a decomposition approach for the route guidance task, which effectively reduces the state space of the route guidance system.

However, in studies on route guidance during incidents, two significant research gaps have been identified: the lack of consideration for the correlation between paths during incidents and the insufficient evaluation of induction measures on network reliability. The former involves not considering the associated road segments between alternative paths, which may lead to congestion on new road segments, thereby causing network failures. The latter gap highlights the rare assessments of how strategies such asrerouting and traffic management affect the overall reliability and performance of transportation networks, particularly under incidents. Bridging these gaps promises advancements in creating more resilient and efficient route guidance solutions.

To address the aforementioned research gaps, this study proposes a route guidance model with limited overlap to improve freeway network reliability under traffic incidents. Specifically, in order to explore alternative paths, we conducted a study on the problem of finding k-short paths with limited overlap. The aim is to identify a set of k-paths that are both sufficiently dissimilar to each other and as short as possible. Then, we promptly updated the route guidance information using a stochastic dynamic traffic assignment model that aligns with travelers' path choice psychology. Moreover, we employed the travel time buffer index as an indicator to evaluate the effectiveness of the guidance strategy, and we conducted a comparison of the travel time buffer index under various induction strategies. A case study on the freeway network in Jinan city is conducted to validate the performance of the proposed model, and the results of the experiment have proven effective in mitigating traffic congestion arising from incidents and perform well in regard to the reliability of the road network under the impact of incidents. In addition, the proposed model has the potential to be a more effective tool in freeway network management under traffic incidents. It can provide a theoretical basis and technical support for developing schemes for freeway network control under incident conditions, thus relieving the impact of traffic congestion on the road network, and enhancing the operational efficiency and safety.

The rest of this paper is organized as follows. First, a literature review on related work is presented in Section 2. Then, the methodology is described in Section 3. The experimental results are shown in Section 4. Finally, some conclusions and remarks of this study are summarized in Section 5.

2. Literature Review

2.1. Route Guidance Strategies. There are two types of route guidance strategies: predictive and reactive [15]. Predictive refers to the utilization of current traffic information to build a predictive model that forecasts future traffic conditions within a specific timeframe. The objective is to proactively implement corresponding measures prior to the occurrence of congestion events. The reactive model involves using real-time dynamic information collected from existing roads to respond promptly to current congestion events by recommending the most efficient route for travelers in that specific environment, aiming to prevent the occurrence of more widespread traffic congestion. The specific algorithms for route guidance encompass several strategies, namely, the average speed route guidance [16], congestion ratio route guidance [17], vehicle quantity route guidance [18], spatial flux route guidance [19], vacant length route guidance [20], and ant colony optimization route guidance [21].

Finding alternative routes is a critical step in route guidance strategies. The primary objective of providing alternative routes is to identify the set of k-shortest paths in the road network [22]. However, in most cases, the resulting path often covers the same segments. Alternative routing has been approached in the existing literature from various perspectives. k-shortest path finding is an extension of the path-finding problem. k-shortest algorithms generate a set of paths in a nondecreasing order of cost between a specified source and a destination pair [23]. Yen [24] proposed an algorithm that introduced the concept of deviation path in the research of the k shortest path routing problem. This algorithm serves as a baseline for many researchers to propose new methods for finding K-shortest paths in various environments. To avoid potential congestion on specific road segments, evacuation plans should include alternative paths that overlap as little as possible when using k-shortest paths to solve the traffic guidance problem. Therefore, the focus of these studies lies in the problem of identifying k-shortest paths with limited overlap. The objective is to find a set of k-paths that are sufficiently distinct from each other while also being as short as possible.

2.2. Network Performance. Traffic incidents often have a substantial influence on freeway networks through various means, such as the degradation of road infrastructure and reduction of road capacity. This leads to extensive traffic congestion, resulting in vehicle delays and posing adverse consequences on road traffic safety and transportation efficiency. In order to evaluate the performance of freeway networks after disruptions, it is important to establish a precise definition of the concept that characterizes the system performance of road networks postdisruption. Then, the indicators employed to measure the system performance of road networks need to be clarified. Based on existing research literature, Gu et al. [25] summarized that reliability, vulnerability, and resilience are the three theoretical concepts extensively used for studying the system performance of road networks following disruptions.

Network reliability refers to the ability of a road network to provide various services that meet the travel needs of users under specified conditions and within a designated timeframe. It is one of the important indicators for measuring the quality of a road network [26]. Numerous random factors affect the network performance of transportation, such as traffic incidents, congestion, and road maintenance. These factors result in an unstable traffic flow state, causing the "unreliability" of travel time for individuals. Reliability, as an important probabilistic indicator, can effectively evaluate the operational status of transportation networks, particularly when changes in external factors lead to variations in traffic demand and road supply conditions. In these cases, a comparison based on the probabilistic method is more applicable. Modern urban road networks are increasingly large and complex, and people have higher requirements for travel quality, which highlights the issue of road network reliability [27]. With the development of society, there is a growing demand to enhance the quality of road network services and improve the adaptability under daily conditions. More and more attention has been paid to the study of traffic reliability under daily conditions, and various reliability concepts such as travel time reliability, network capacity reliability, and smoothness reliability have been proposed and widely applied [28].

Travel time reliability is a measure of whether a transportation network is reliable from the perspective of travelers, focusing more on road users. Bell [29] defined travel time reliability from a probabilistic perspective as the probability that a traveler can reach their destination within a certain level of service and travel time. Travel time reliability can supplement for the shortcomings of connectivity reliability in depicting the operational state of transportation systems, and it provides a more direct reflection of the road network's operational status compared to capacity reliability. The study of travel time reliability can be divided into two research directions: simulation methods and analytical methods. These approaches are based on the differences between models generated using virtual traffic models or models constructed using real data [30].

In the study of travel time reliability, the simulation method relies on indicators such as mean, variance, and standard deviation to calculate reliability. This method does not depend on the quantity or quality of data, making it flexible and convenient, which has drawn the attention of researchers. Inouye [31] conducted research on travel time reliability based on the assumption of stochastic user equilibrium. It defined travel time reliability as the probability that the travel time between the origin and destination does not exceed the standard travel time corresponding to each level of service. The proposed travel time reliability model was applied to the Hanshin area highway network to evaluate the planning of new routes from the perspective of travel time reliability. Other researchers conducted travel time distribution tests based on a large amount of measured data. Park et al. [32] used a multistate travel time reliability model to study the correlation between traffic incidents and travel time reliability. However, there is insufficient research on the utilization of reliability for evaluating traffic guidance strategies.

3. Methodology

Figure 1 shows the framework of the method proposed in this study. It includes three main parts: (1) First, we assess the need for guidance using the road network, traffic flow data, and incident characteristics. If guidance is necessary, we calculate the volume of traffic that needs to be directed. (2) developing route guidance strategies involves analyzing these elements and (3) evaluate road operational efficiency and network performance to determine when to end the route guidance. In the following sections, this paper presents an alternative path algorithm with limited overlap, which aims to find a set of k-paths that are both sufficiently dissimilar to each other and as short as possible. It is followed by a stochastic user equilibrium model which considers both the impact of traffic flow on travel time and the perceptual error of travelers. Then, route guidance processes are introduced in detail.

3.1. Route Guidance Strategies. Once a traffic incident occurs on the freeway, there are two potential approaches available to the management personnel for addressing the situation: it is recommended that travelers wait or proceed slowly when passing through the incident section, or alternatively, provide detour routes for drivers. First, in order to facilitate alternative routes for travelers, it is necessary to designate the off-ramps located upstream of the incident section as diversion points. Subsequently, alternative routes are explored within the road network to divert the traffic flow. Then, based on the duration and other characteristics of the traffic incident to ascertain the appropriate amount of traffic diversion, we ultimately, employed the traffic assignment method to effectively distribute the amount of traffic diversion on all alternative routes.

3.1.1. Alternative Path Routing. First, it is necessary to explain how to calculate the travel time. The best-known model for road link travel time is a function proposed by the US Bureau of Public Roads, known as the standard BPR function as shown in the following equation:

$$t_a = t_0\left[1 + \alpha \cdot \left(\frac{V_a}{C_a}\right)^{\beta}\right], \tag{1}$$

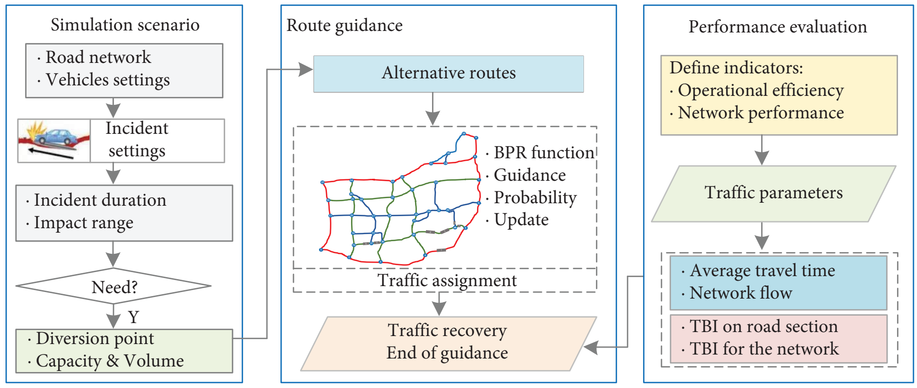


Figure 1: The framework of the method.

where t_a is the average travel time per unit distance under normal conditions on link a (s/km); t_0 is the free-flow travel time (i.e., the travel time at zero flow) per unit distance under normal conditions on link a (s/km); V_a and C_a are the demand volume and capacity; parameter α determines the ratio of free-flow travel time to the travel time at capacity; and parameter β determines how rapidly travel time increases from the free-flow travel time. These parameters are empirically defined as $\alpha = 0.15$ and $\beta = 4$.

The problem of finding K-alternative path routing is a generalization of the shortest path problem. In a given weighted and directed network, the problem of finding the K-shortest paths involves determining a set of k-shortest paths between a specified origin and destination. The commonly used algorithm to solve the K-shortest path problem is Yen's algorithm based on the deviation path concept [23]: (1) using Dijkstra's algorithm to calculate the shortest route between the origin and destination and (2) then determining all other K-shortest paths. Here, to find the k^{th} route A_k, the algorithm assumes that all paths from A_1 to A_{k-1} have previously been found. The k iteration can be divided into two processes: finding all the deviations A_{ki} and choosing a minimum cost path to become A_k.

However, employing the aforementioned method to obtain K-shortest paths can lead to similarity, as multiple paths may share the same edges. In the case of path-induced traffic diversion, this can lead to a concentration of traffic flow on a particular segment, resulting in congestion on newly affected segments. To avoid this condition, we conducted a study on the problem of finding K-shortest paths with limited overlap. It should be noted that "overlap" refers to the extent to which two paths share common road segments. This concept is quantitatively defined by a similarity threshold ratio, which compares the length of road segments shared between two paths with the total length of one of the paths. Our goal was to identify a set of k-paths that satisfy the following two criteria: (a) they are sufficiently dissimilar to each other based on a user-defined similarity threshold R and (b) they are as short as possible.

The similarity threshold R is defined as the ratio of the combined length of road segments shared by the k^{th} path and the predetermined detour paths to the total length of the k^{th} path, as indicated by the following equation:

$$R_{ij} = \frac{l_{ij}}{l_j}, \quad (2)$$

where R_{ij} represents the similarity threshold of the two paths i, j, l_{ij} represents the length of road segments shared with j, and l_j is the total length of the j path. The computation process of K-shortest paths with limited overlap is depicted in Figure 2. By setting a similarity threshold, one can filter out paths that are too similar to each other based on shared road segments, thereby encouraging the identification of alternative routes that provide different options for detouring or navigating from a start point to an endpoint.

In this study, extensive experimentation was conducted, taking into account the road network's scale and the availability of alternative routes. Based on these factors, we have decided to present the outcomes where the R value is set at 0.5.

3.1.2. Traffic Assignment. When receiving traffic guidance, drivers engage in a comprehensive evaluation, taking into account their individual travel requirements, assessments of traffic conditions, and psychological cognition, in order to determine whether to follow the provided guidance. Consequently, the likelihood of travelers selecting a specific route can be expressed probabilistically. The logit random path choice model is a standard probabilistic allocation model that takes into account the tendency of real-life drivers to select the path they subjectively perceive as having the lowest impedance, and here, we represent it as C_k^{rs}. If we assume that the minimum impedance of the path between origin and destination is represented by k, then the value of C_k^{rs} can be obtained using the following equation:

$$C_k^{rs} = c_k^{rs} + \lambda_k^{rs} \quad \forall k, r, s, \quad (3)$$

where c_k^{rs} represents the actual impedance of the path and λ_k^{rs} means the difference between subjective perception and actual path impedance (λ_k^{rs} represents the random error component, $E(\lambda_k^{rs}) = 0$).

Based on random utility theory, we make the assumption that the random error term λ_k^{rs} follows the Gumel distribution, allowing its incorporation into the polynomial logit model. The perceived path impedance by travelers is determined by the interplay of path flow and path impedance, as

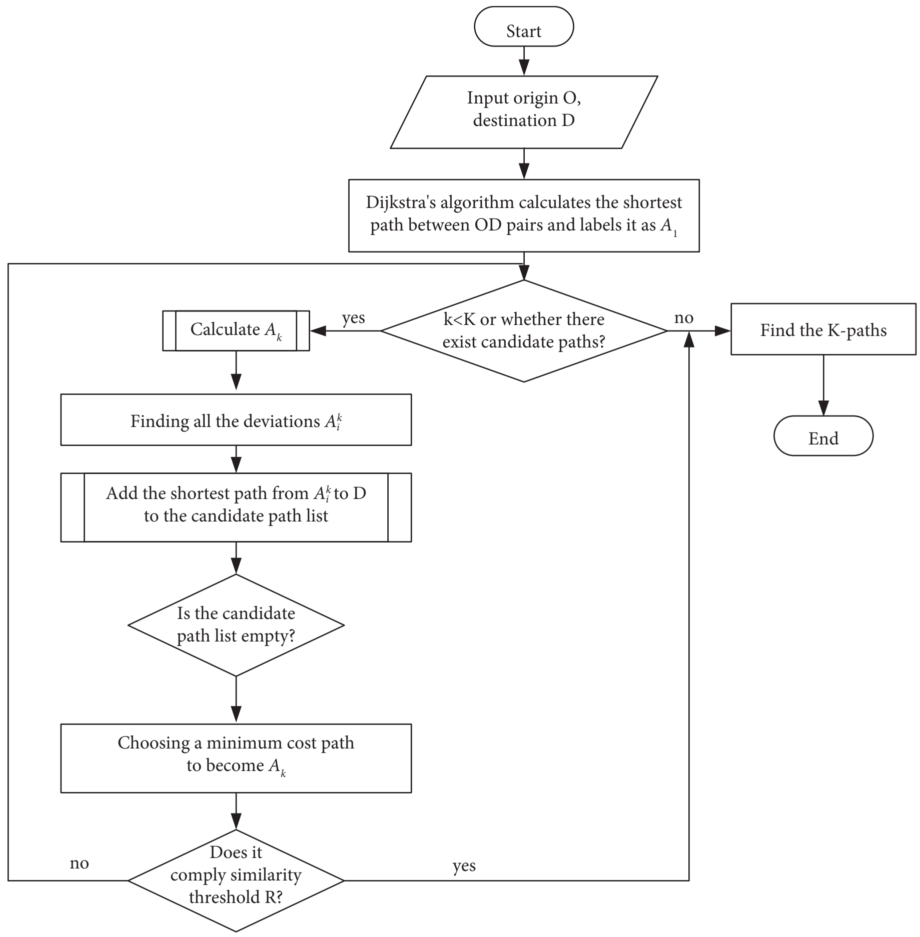


Figure 2: Flowchart of calculating alternative routes.

expressed in equation (4). In this equation, the discrete parameter $\delta = 1$ reflects the level of aggregation in travelers' comprehension of impedance. Equation (5) represents the probability of travelers selecting path k, where θ means the allocation parameter, and in this case, it is taken as 4.

$$C_k^{rs} = c_k^{rs} + \frac{1}{\delta}\ln f_k^{rs} \quad \forall k, r, s, \tag{4}$$

$$p_{rs}^k = \frac{\exp\left(-\theta c_{rs}^k\right)}{\sum_{l \in P_{rs}} \exp\left(-\theta c_{rs}^l\right)}. \tag{5}$$

It is known that when a traffic incident occurs, where there are n alternative routes available from the incident location to the destination, with a diversion flow of Q, we can determine the diversion flow for each alternative route by utilizing the probability of drivers selecting each route, as specified in the following equation:

$$Q_k = \frac{P_k}{\sum_{k=1}^{n} P_k} * N_0, \tag{6}$$

where Q_k means the diverted flow of the k^{th} alternative route and N_0 represents the overall traffic flow that needs to be redistributed to alternative paths due to traffic incidents.

3.1.3. Traffic Guidance Process. As previously mentioned, the primary steps for completing path guidance encompass the identification of diversion points, calculation of diversion paths, determination of diversion volumes, and execution of traffic distribution, and the specific process is depicted in Table 1. Several significant points deserve attention in this context. First, the triggering of the guidance mechanism can mainly be divided into incident-triggered mechanism and time-triggered mechanism. In this paper, we initiate the guidance strategy through the time-triggered mechanism, which implies that we determine the starting time of guidance based on the timing set and reflected by the freeway department manager after the occurrence of an incident. Furthermore, the guidance discussed in this paper is an ongoing dynamic process. Over time, changes in road capacity and traffic conditions significantly impact the value of the Bureau of Public Roads (BPR) function, subsequently influencing the probability of path selection during traffic distribution. Therefore, this guidance process is dynamically changing.

3.2. Performance Evaluation. In this paper, traffic guidance methods are evaluated from the perspective of road network performance, considering two dimensions of road network, efficiency and reliability. Road network operational efficiency is essentially a measure of the ability of

Table 1: Route guidance procedure.

Step	**Initial Input**: Network parameters (topology, free-flow speed, and capacity); OD information (demand, origin, and destination); Detector setup (lane position and detector type)
1	**SUMO** simulator: generate vehicle trajectories **For** all link a, and vehicle f:
2	Statistical time interval and the traffic diversion N_0
3	**Initialize** a dict to store data, including edge flow and edge impedance
4	**Collect statistical** data on $Volume$, $waiting\,time$, and $travel\,speed$
5	Guide based on the type of incidents
6	During the guidance period, with a time interval of 5 minutes: First, **calculate** travel time on link a: t_a $t_a = t_0 \cdot [1 + \alpha \cdot (V_a/C_a)^{\beta}$ Then, **calculate** route impedance and the probability of choosing the k^{th} path $C_k^{rs} = c_k^{rs} + \lambda_k^{rs}$ $p_{rs}^k = \exp(-\theta c_{rs}^k)/\sum_{l\in P_{rs}}\exp(-\theta c_{rs}^l)$ **Allocate** vehicles to the guided path based on the p_{rs}^k $Q_k = (P_k/\sum_{k=1}^{n} P_k) * N_0$
7	**Update** the p_{rs}^k according traffic volume.
8	Control vehicle operation until the guidance is completed
9	**Output** the operational data
10	End

a transportation system to meet the traffic demand or traffic volume within a unit of time or at a unit cost. The evaluation of traffic operational efficiency often involves elements such as time and vehicle flow volume, and here we use average travel time and traffic volume on the road network as indicators of traffic efficiency.

The travel time buffer index describes the operational status of the regional road network, and we can calculate it by using the following method. First, we need calculate travel time buffer index of road section by using equation (7): TBI_j means the travel time buffer index of road section j, $t_{0.95,j}$ represents the 95$^{\text{th}}$ percentile travel time for road section j, $\overline{t_j}$ is the average travel time of road section, and t_j^f means the travel time under free-flow conditions.

$$TBI_j = \frac{t_{0.95,j} - \overline{t_j}}{t_j^f}. \tag{7}$$

Then, the length of road section is used as weight, and the reliability in road travel time of each type is calculated. In this section, we calculated TBI_{freeway}, TBI_{trunk}, and TBI_{primary}.

Finally, we need to weight the reliability index of road travel time of each level with the vehicle kilometers traveled (VKT) ratio as the weight to calculate the reliability index of road network travel time. It should be noted that the VKT calculation includes the following steps: first, we calculate the VKT value for each road segment during the statistical period, where $VKT_{ai} = V_{ai} \cdot L_{ai}$, in which V_{ai} represents the number of equivalent passenger cars passing through segment ai during the statistical period and L_{ai} is the length of segment ai. Second, we aggregate the VKT values for freeway, expressed as $VKT_{freeway} = \sum_{i=1}^{N_i} VKT_{ai}$, where N_i is the number of segments on the highway. Similarly, we calculate VKT values for trunk and primary roads. Third, we compute the percentage of each road type's VKT in relation to the total VKT.

The travel time reliability reflects the volatility of traffic operations in the road network, and a higher value indicates a higher level of unreliability.

4. Simulation and Results

4.1. Experimental Design

4.1.1. Overview of Experimental Design. Given the challenge of validating the proposed route guidance method in real road networks, we use the traffic simulator SUMO in this section to employ evaluation. As a widely adopted open-source simulator, it offers a convenient representation of multimodal traffic and supports easy extensibility through multiple programming languages. Before conducting the simulation, it is crucial to generate a SUMO network file, which accurately describes the traffic elements in the map, including roads and intersections traversed by vehicles. Subsequently, it becomes essential to provide a description of the vehicles, a process commonly known as demand modeling. When running the simulation, the Python agent collects real-time traffic data at time intervals, sourced via the configuration of detectors. The Python program will transmit the collected data to the controller in the appropriate format, enabling the execution of algorithms that yield a new state in return. The Python agent collects the data once again, followed by the activation or deactivation of services in SUMO for simulating other time intervals, and this process continues iteratively. After the simulation is completed, the operational data are collected and the relevant key performance indicators are calculated.

The aim of this study is to investigate the methods of freeway route guidance during incident conditions. This requires the use of SUMO script code for simulation, road network modeling to represent the transportation infrastructure, traffic flow modeling to capture the dynamics of vehicular movement, and numerical calibration to validate the models and ensure accuracy. This section introduces road network modeling, traffic demand modeling, and simulation scenario configuration as follows.

4.1.2. Road Network. To achieve an accurate reproduction of the real road network, the road network data utilized in this study were collected from Jinan city, Shandong Province. In order to simplify the research process, low-level branch roads were excluded from the road network while maintaining overall accessibility. The road network was built using the SUMO tool NETEDIT, and the information comprises road names, road classes, road lengths, segment speed limits, number of lanes, and additional parameters. This study aims to investigate the road network surrounding the G2001 Jinan Ring Freeway, which is depicted in Figure 3. The road network also contains other freeways, trunks, and primary roads.

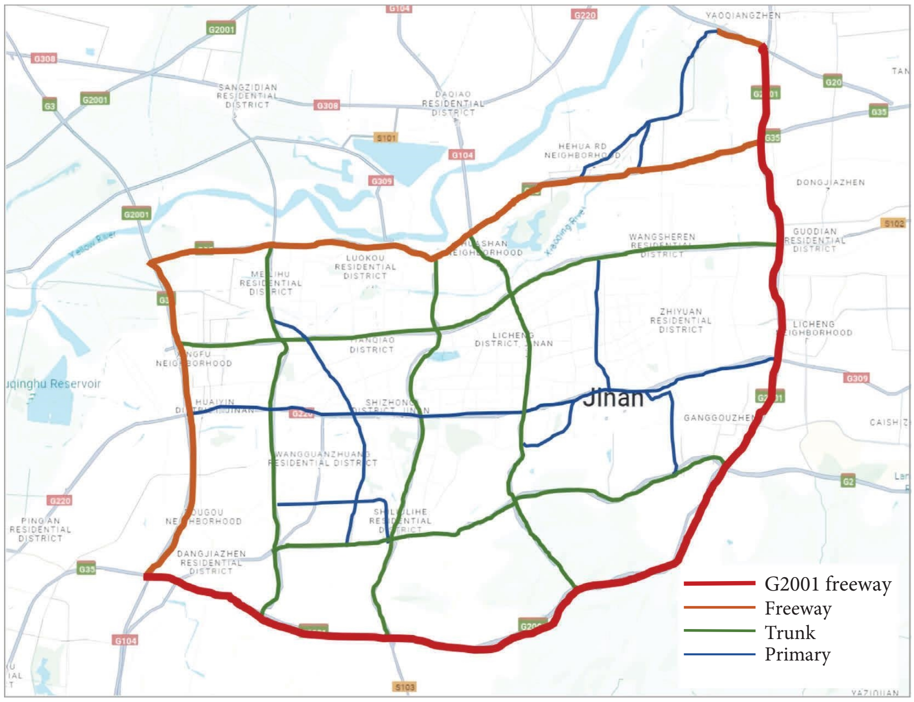


Figure 3: Simulation of freeway network in Jinan city.

To collect traffic state data, the installation of road detectors is essential. In this study, we have deployed induction loops and lane-area detectors. The induction loop detector in simulation has the capability to detect and measure various parameters related to traffic flow, including traffic volume, occupancy rate, average speed (both time-based and spatial-based), average vehicle length, and the number of vehicles passing through. The lane-area detectors have similar functions to a camera, allowing for the monitoring of traffic conditions in one or multiple lanes. The data collected in this paper using this detector include tracking the number of entering and exiting vehicles and calculating the average speed and occupancy rate. Both types of detectors aggregate data every 300 seconds, making the collection and analysis of traffic data much more efficient.

4.1.3. Vehicle Parameter Settings. Another thing that needs to be explained in the simulation is how to define the vehicles running in the road network. The utilization of precise car-following and lane-changing models can enhance the conformity of traffic flow within SUMO simulation to real-world road operations. This study uses the SUMO IDM car-following model and four-layer lane-changing model referred to as LC2013 or JE2013 to model the behavior of vehicles. Both models are stochastic to account for the human behavior. Table 2 displays the parameters included in the model.

4.1.4. Incident Settings. According to Wright [33], traffic incidents are the main contributing factors to traffic congestion. The distribution of road sections experiencing a capacity decrease due to traffic incidents is often random. Furthermore, longer incident durations result in more severe consequences. In accordance with the Highway Capacity Manual [34], incidents such as crashes, disabled vehicles, and debris are classified as situations that cause a reduction in capacity. These instances are regarded as nonrecurring. Various scholars have provided different definitions for the specific content of incidents in their studies. Nevertheless, the primary characteristics of incidents can be identified as reduced capacity and random occurrences.

Considering the objective of this paper, which is to investigate traffic guidance methods using simulation techniques, here we assume these parameters and simplify the analysis of the impact on incident capacity size and duration time. Initially, a road segment on the Jinan Ring Freeway under study is randomly selected. Specifically, the road segment with an incident vehicle in Figure 4 is chosen. It is assumed that a traffic incident takes place at a specific location on the segment, lasting for 60 minutes. The duration is considered the most objective characteristic for describing the impact of an incident on normal traffic operation. It is comprised of four stages: discovery time, response time, clearance time, and recovery time. In this simulation, the duration is approximated as the time when a lane or road is closed. For this study, we devised two types of incidents to judge whether they hindered the operation of a lane or a road segment. Table 3 displays a decrease in road capacity for two scenarios [35].

4.2. Simulation Results and Analysis. Here, it is necessary to provide an explanation for the statistical analysis of the simulation results. Since the road conditions remained the same before the implementation of traffic guidance, data

Table 2: Calibration parameters list.

Parameters	Description	Value or range
accel	Acceleration of vehicles (in m/s^2)	2.6
decel	Deceleration of vehicles (in m/s^2)	4.5
minGap	Empty space after leader (in m)	[2, 3]
tau	Driver's desired (minimum) time headway	[1, 2]
sigma	Driver's imperfection	[0, 1]
lcStrategic	Eagerness for performing strategic lane changing	[0-inf)
lcCooperative	Willingness for performing cooperative lane changing	[0-1]

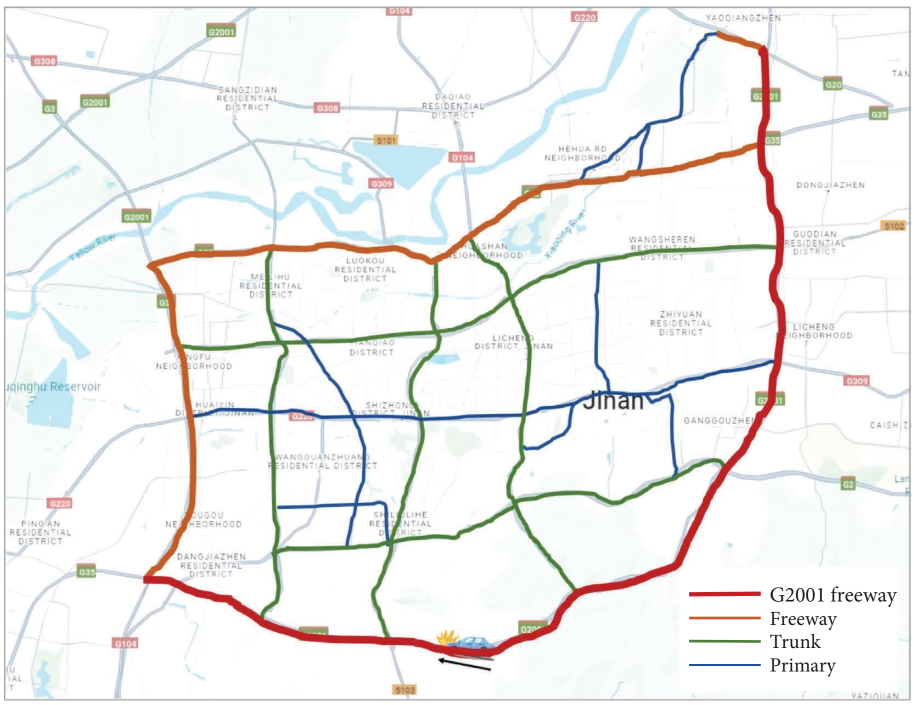


Figure 4: Incident location.

Table 3: Simulation incidents parameter settings.

Scenario	Duration time (s)	Proportion of freeway segment capacity remaining
1 lane blocked	60	0.35
2 lanes blocked	60	0

collection started 5 minutes prior to the initiation of the route guidance and continued until 15 minutes following the end of the incident.

In addition, this paper compared the alternative path selection algorithm with some fundamental algorithms. They are the Yen's algorithm, the A^* algorithm, and the ant colony algorithm, respectively. The ideas of these algorithms are described as follows. The route guidance model with limited overlap that we proposed in this study is abbreviated as LO.

The commonly used algorithm to solve the K-shortest path problems is Yen's algorithm based on the deviation path concept [23]. It includes two parts: (1) using Dijkstra's algorithm to calculate the shortest route between the starting and ending points and (2) determining all other k-shortest paths. Here, to find the A_k, the algorithm assumes that all paths from A_1 to A_{k-1} have previously been found. The k iteration can be divided into two processes: finding all the deviations A_{ki} and choosing a minimum cost path to become A_k.

A^* is a graph traversal and path search algorithm. It does this by maintaining a tree of paths originating at the start node and extending one edge at a time until it finds a path to the given goal node having the smallest cost. Then, we can obtain the shortest K-paths by obtaining a sorted list of the shortest paths.

In the ant colony algorithm, every ant is considered a search agent, selecting paths based on heuristic rules and leaving pheromones on these paths to guide other ants' choices. In general, shorter paths have higher pheromone

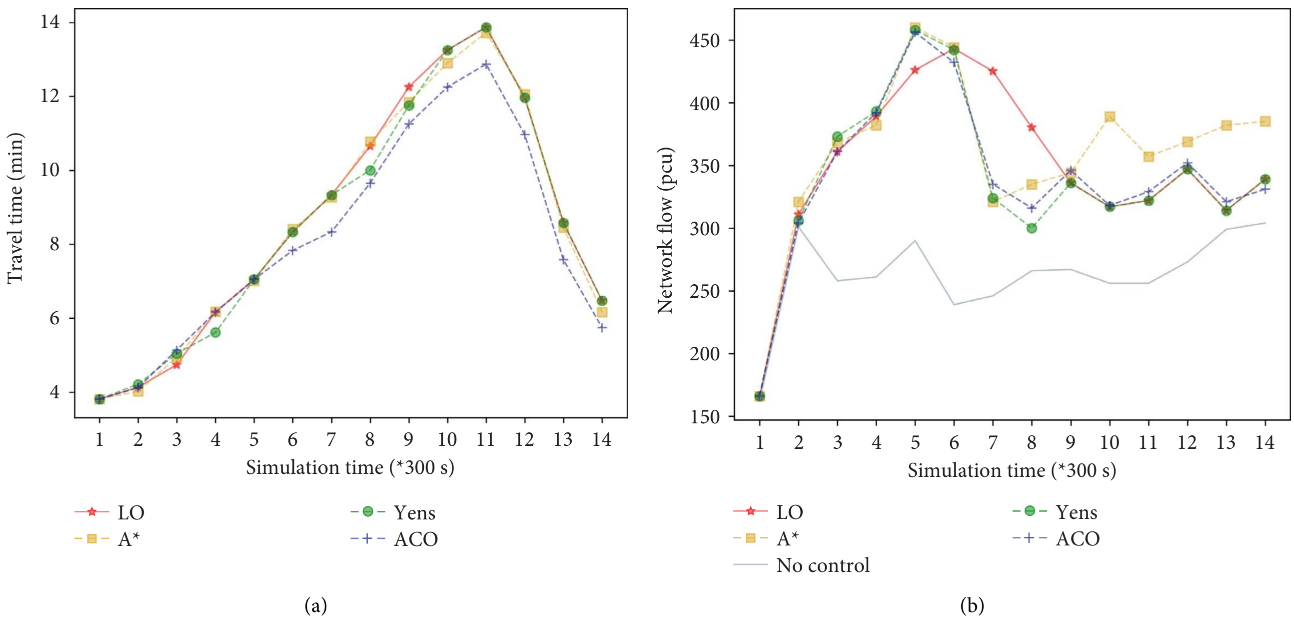


Figure 5: Network efficiency with different route guidance in the scenario with single lane blocked. (a) Average travel time. (b) Network flow.

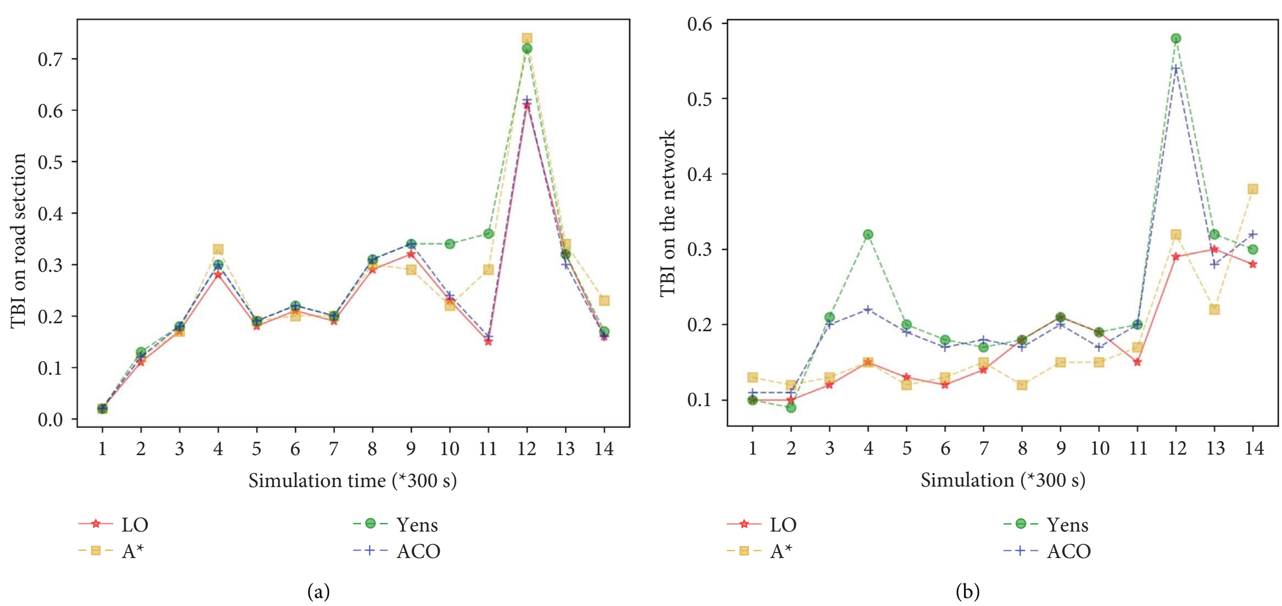
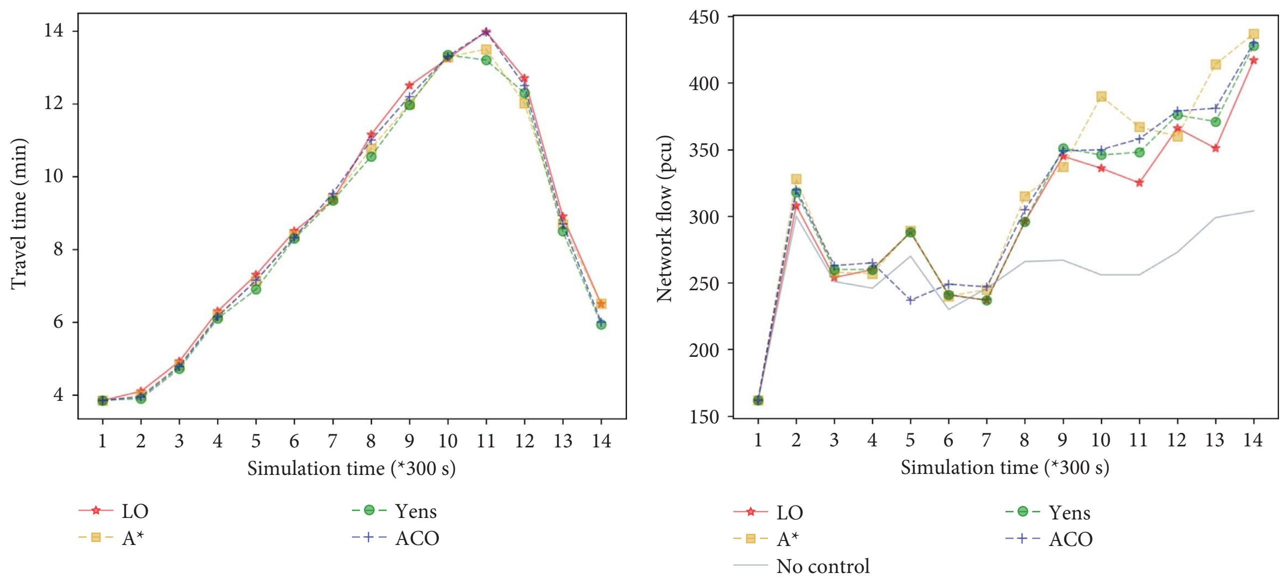


Figure 6: Network reliability with different route guidance in the scenario with single lane blocked. (a) TBI on road section. (b) TBI for the network.

concentrations. The concentration of pheromones on the superior paths increases gradually, thereby enticing a greater number of ants to select those paths. Consequently, the concentration of pheromones on the superior paths progressively increases throughout the iterative process, thereby enticing a greater number of ants to select those paths and facilitating the identification of the globally optimal path. Upon the completion of the iteration process, we can retrieve the K shortest paths from the recorded list.

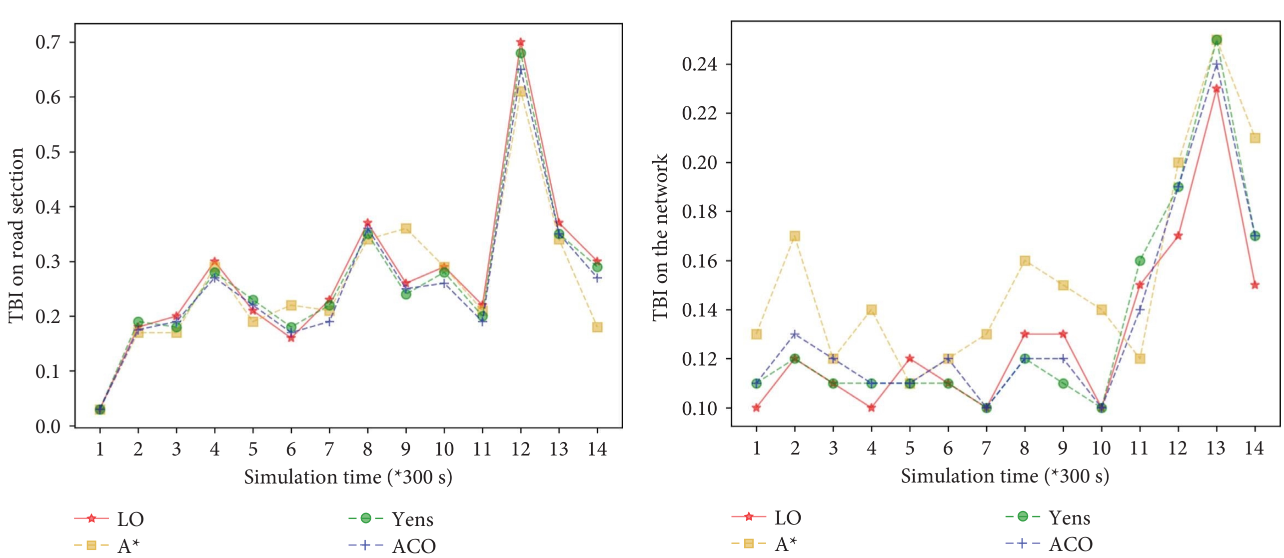
For this study, we devised two types of incidents to observe whether they hindered the operation of a lane or a road segment, and the incident settings are thoroughly detailed in Section 4.1.4. In addition, the lack of traffic guidance can cause congestion on diversion routes, resulting in significant differences in travel time, network reliability, and other indicators compared to using guidance method. Lane closures due to incidents can significantly increase travel times on diverging sections and affect the network's



(a)

(b)

Figure 7: Network efficiency with different route guidance in the scenario with road blocked. (a) Average travel time. (b) Network flow.



(a)

(b)

Figure 8: Network reliability with different route guidance in the scenario with road blocked. (a) TBI on road section. (b) TBI on the network.

travel time reliability, with both metrics increasing significantly. Presenting the findings in a chart may detract from the clarity of comparing the algorithms. Given the paper's emphasis on comparing algorithms, details on section travel times and travel time reliability in scenarios without guidance are omitted to clarify the distinctions between methodologies. However, traffic volume across the road network is a very macroscopic indicator. Displaying this result does not detract from the intuitive comparison of algorithms; thus, it is retained to illustrate the effectiveness of the guidance provided.

4.2.1. The Scenario with Single Lane Blocked. In terms of road network operational efficiency, timely implementation of route guidance measures after incidents can effectively alleviate congestion on affected road sections. Figure 5 shows the results of the average travel time of the diverging section, and the traffic volume on the road network. Figure 5(a) demonstrates a gradual increase in travel time on diversion routes throughout the duration of the traffic incident. When the incident clears, the travel time of vehicles on the incident section starts to decrease. The route guidance method based on the ant colony algorithm performs the best here, manifested by a slow increase in travel time on the diverging section, and a quicker decrease in travel time after the incident is resolved. Figure 5(b) indicates that all route guidance measures significantly increase the traffic volume in the road network, with the route guidance strategy based on the A^* algorithm performing the best in this aspect.

Furthermore, traffic guidance enhances the reliability of the road network, as depicted in Figure 6. Figure 6(a) displays the travel time buffer index on the diverted section, with a significant increase in the 12th data value in the figure attributed to the incident section unblocked after clearing of the incident. The differences in the reliability of diverted road sections under various guidance methods are minimal. This likely occurs because traffic guidance mainly prevents new congestion without significantly relieving the stress on road sections diverted due to incidents. Figure 6(b) represents the results of the travel time buffer index of the road network, and the reliability shows significant fluctuations when the section is unblocked. The proposed approach, which takes into account the similarity threshold R, improves the reliability of the road network. The guidance strategy based on the A^* algorithm achieved relatively good results here, while the reliability of the method we proposed showed less fluctuation.

4.2.2. The Scenario with Road Blocked. Implementing route guidance can improve the operational efficiency of the road network in the scenario with road blocked. The results depicted in Figure 7 illustrate the average travel time and the traffic volume on the road network for this scenario. Figure 7(a) demonstrates a gradual increase in travel time on diversion routes throughout the duration of the traffic incident and when the incident clears, the travel time on the diverging section starts to decrease. In contrast to the findings in the scenario with single lane blocked, no significant differences were observed among various route guidance algorithms. Figure 7(b) indicates that all route guidance measures have significantly increased the traffic volume on the road network. Among them, the route guidance strategy based on the A^* algorithm also performs the best in this aspect.

Taking route guidance measures also increases the reliability of the road network. Figure 8 illustrates the findings regarding the reliability of travel times for both the diversion road section and the entire road network. Figure 8(a) presents the buffer index of travel times for the diversion section, showing a significant increase at the 12th data value in the figure caused by the unblocking of the incident section. Since traffic guidance only avoids creating new congestion without relieving the pressure on road sections diverted due to incidents, the reliability of road sections under various diversion strategies does not show significant differences. Within the results of the road network reliability index depicted in Figure 8(b), it remains apparent that the method based on the similarity threshold R, that we proposed, exhibits superior performance. It is evident that considering the overlap between road sections can lead to better network performance when guidance under incidents is implemented.

Through experiments conducted with the involvement of two traffic incidents, we have found that it is necessary to promptly implement route guidance measures to reduce the impact of incidents on the road network. Regarding the traffic efficiency outcomes of guidance following two types of incidents, it is initially evident that implementing guidance is essential. This is because traffic guidance can significantly enhance the traffic volume of the road network, as demonstrated in Figures 6(b) and 8(b). Second, when an incident occurs, not providing guidance could likely lead to vehicles queuing and spilling over into upstream sections. Implementing guidance on diverted sections can effectively prevent this scenario. Timely directing vehicles to diversion paths can alleviate pressure on upstream sections. In terms of travel time on diverted sections, the ACO algorithm performed well in the scenario with single lane blocked. However, in the scenario with road blocked, there were no significant differences between the various algorithms.

Observing the reliability indicators for two types of incidents, it is evident that the TBI for diverted road sections does not show significant differences among various methods. This is because each guidance strategy starts at the same time, and the choice of diversion path does not affect the number of vehicles on the diverted sections. However, the proposed path guidance modeling, which takes into account the similarity threshold R, demonstrates good performance in regard to the reliability of the road network in both of the incidents. The results indicate that diversion methods based on overlapping paths can effectively enhance the network's performance.

Overall, implementing traffic guidance measures can enhance the operational efficiency and reliability of the entire road network. However, different guidance strategies exhibit varying performances across multiple evaluation criteria. A method that performs well in terms of network efficiency might not necessarily yield the best results in network reliability. This suggests that there might not be a direct correlation between efficiency and reliability goals when formulating control strategies. The findings imply that enhancing the management of road network reliability and traffic efficiency requires different approaches. From a traffic network operation perspective, network performance should be prioritized, requiring a comprehensive consideration of desired control objectives when selecting route guidance strategies.

5. Conclusion

In this study, a route guidance model with limited overlap to improve freeway network reliability is proposed. To avoid potential congestion on specific road segments, this study focuses on the problem of finding k-shortest paths with limited overlap, which takes into account the similarity threshold. Furthermore, the guidance discussed in this paper is an ongoing dynamic process. Over time, changes in road capacity and traffic conditions significantly impact the value of the BPR function, subsequently influencing the probability of path selection during traffic distribution. Therefore, this guidance process is dynamically changing. Experimental studies were conducted on the Jinan freeway network to illustrate the model. It assesses two types of incidents to determine whether they hindered the operation of a lane or a road segment. The result demonstrates the following: (1) this new modelling substantially enhances the capacity and efficiency of the traffic networks and counters traffic congestion. The distribution of vehicles is more homogeneous; (2) the proposed path guidance modelling demonstrates good performance in regard to the reliability of the road network in both of the incidents; (3) however, it does not perform optimally in terms of road network operational efficiency and is not ranked as the top performer. This indicates that there may not be a positive correlation between the goals of efficiency and reliability when formulating control strategies. The findings imply that enhancing the management of road network reliability and traffic efficiency requires different approaches.

The innovations of this new route guidance modelling are demonstrated in two aspects. First, a route guidance model with limited overlap is proposed to improve freeway network reliability under traffic incidents. Second, the guidance discussed in this paper is an ongoing dynamic process. Over time, changes in road capacity and traffic conditions significantly impact the value of the BPR function, subsequently influencing the probability of path selection during traffic distribution. The results of this study contribute to providing a theoretical basis and technical support for developing schemes for freeway network control under incident conditions.

Further studies are required for the perfection of the proposed model. In the future research, we will study traffic route guidance in more complex incident scenarios by learning more about the operational impact of incidents on the freeway network. Moreover, we will extend the definition of alternative routing by considering multiple criteria and constraints to match the requirements of a wider range of applications. Finally, we attempt to establish a comprehensive network quantification metric to evaluate traffic guidance strategies.

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 regarding the publication of this paper.

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