Considering the Characteristics of Traffic Risk Factors and the Method of Establishing a Flexible Traffic System

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With the acceleration of urbanization and the development of the automobile industry, the contradiction between the traffic capacity of existing urban roads and the growing traffic demand has become increasingly acute. Traffic congestion is becoming increasingly prominent. The purpose of this article is to consider the characteristics of traffic risk factors and to study the method of establishing a flexible traffic system. It can relieve traffic congestion and provide a smooth and orderly traffic environment using intelligent transportation systems to control and direct traffic flow. Based on the large urban road network, this research uses the theory of coordinated control and learning mechanism, fuzzy control, dynamic reprogramming, and other theories to study phase sequence, balance peripheral load, and overall traffic flow. It also uses on-board sensors to optimize the collection and processing of network information, decompose traffic guidance work, select the optimal route, and autonomously guide the intelligent transportation system. Under the flexible demand scheme, the average load of the trunk road is reduced by a larger degree, which is 4% lower than that of the fixed demand scheme. At the same time, the average load of the branch has increased more, which is 4% higher than that of the fixed demand scheme. It can be seen that under the elastic demand scheme, the distribution of traffic flow in the road network is more balanced and the optimization effect of relieving traffic pressure on trunk roads and improving the utilization rate of branch roads is more significant.

1. Introduction

With the development of science and technology and the national economy, the functions of automobiles have been continuously improved. Its price gradually decreased, and its quantity increased year by year. Statistics released by the Ministry of Public Security show that by the end of 2020, the number of cars in China has exceeded 280 million. The rapid growth of car ownership has also made road traffic under enormous safety pressure and has become a social issue that has attracted wide attention. According to the latest statistics provided by the World Health Organization, there are 1.25 million people killed in road traffic accidents every year worldwide. China is the country with the most road traffic accidents. The huge car ownership makes China bear a greater threat to road traffic safety. Although existing cars are equipped with airbags and seat belts, protection devices such as airbags and seat belts can weaken the injury caused to the vehicle driver in an accident. However, if the car can estimate the driving risk according to the current road environment and actively give feedback to the driver in time, this will avoid or mitigate the impact of the accident to the greatest extent possible.

The purpose of traffic flow operation risk assessment is to explore the internal relationship between road traffic accidents and dynamic traffic flow operation characteristics. It scientifically estimates and predicts the potential risk of an accident, the occurrence process and the postevent impact stage. It is expected to propose systematic traffic safety management measures from the aspects of traffic organization, traffic control, and traffic guidance. In order to reduce the risk probability of the accident before the accident occurs, and reduce the severity of the accident during the accident. It quickly takes targeted accident response
measures after the accident to reduce the impact of the accident. Therefore, the research on the risk assessment method of traffic flow operation plays a very important role in proposing and implementing the strategy of active safety prevention and control of traffic accidents, improving the level of emergency management of road accidents in China, and reducing the degree of harm of traffic accidents.

The innovations are as follows. (1) This article proposes a traffic risk state prediction method based on the M-B-LSTM network. It designs a traffic risk state prediction framework based on parameter prediction. (2) From the perspective of minimizing the delay of traffic flow, the optimization objective function is given and the convex analysis is carried out. It uses the system identification method to obtain segment parameters and uses fuzzy control logic to switch the phase sequence. It designs the distributed cooperative control law of the urban traffic network system and introduces a learning mechanism for optimization. (3) The time-shifted two-stream convolutional neural network based on the attention mechanism is mainly composed of the spatial stream and temporal stream. Spatial flow extracts high-level appearance features of RGB image sequences, and temporal flow extracts high-level motion features of optical flow sequences.

2. Related Work

Liu proposed an urban traffic monitoring system based on participatory perception. Unlike existing efforts that rely heavily on intrusive sensing or the full cooperation of detection vehicles, systems harness the power of participatory sensing to crowdsource traffic sensing tasks to the phones of bus passengers. The system recovers bus travel information based on crowdsourced data from participants. This in turn derives the real-time traffic conditions of the roads covered by the bus lines. The practical experiment of its realization using the prototype proves the feasibility of the system. The system achieves accurate and fine-grained traffic estimation in crowds with moderate perceptual and computational overhead [1]. Jia proposed a new scheme to implement an event-driven traffic ticketing system. The system consists of two modules, namely, an event detection module and a database management module, which are used to perform information retrieval and send traffic tickets. It turns out that his work is efficient and can detect events accurately [2]. Sagkriotis studied a long-range traffic loss model for a dual-link system. The system accommodates calls from a single service class that follow a Poisson arrival process. Each link has two thresholds, which refer to the number of in-service calls on the link. The lowest threshold is called the support threshold. It defines the highest point at which a link can support calls offloaded from another link [3]. From its inception to the present, traffic light control systems have been widely used to monitor and control the flow of vehicles. However, with the increase in the number of public (buses) and private vehicles (cars, motorcycles, and trucks), the population of urban centers is increasing. This phenomenon can lead to traffic congestion and increase environmental and noise pollution. To prevent such problems, Lei aimed to contribute to the improvement of traffic signals by developing a centralized traffic light control system using a unique wireless communication network. To demonstrate the effectiveness of the system, he conducted an analysis of the most common types of urban intersections [4]. Recent studies have shown that macroscopic urban traffic control, especially perimeter control, plays an important role in the field of urban traffic control. Han researched and invented a new data-driven control method called Constrained Model-Free Adaptive Predictive Control (C-MFAPC) for perimeter control of two-region urban traffic systems. In this strategy, he combines the advantages of Model-Free Adaptive Control (MFAC) and Model Predictive Control (MPC). In this framework, he utilized the Macro Fundamental Graph (MFD) to determine the required vehicle accumulation in each area and generate output data for the urban transportation system [5]. Yu proposed a general framework for resolving resource utilization conflicts in air traffic systems, expressed in the form of a maximum plus linear model. For a different purpose, he proposed a general air traffic system optimization model that considers buffer size. The method he proposed aimed to minimize the total system delay to meet demand specifications. It allows air traffic controllers to obtain optimal control strategies to delay the occurrence of input events or change the input rate of system resources [6]. With the continuous development of the economy, people’s living standards have been continuously improved, and their purchasing power has been significantly enhanced. Therefore, more and more people use the car as a way of travel. However, traffic and road resources are limited. Therefore, this will inevitably lead to related problems such as traffic congestion. Chen studied computer vision, the intelligent traffic monitoring system under the intelligent traffic system, and then introduced the related knowledge of the intelligent traffic monitoring system under the intelligent traffic system, and then introduced the related knowledge of the intelligent traffic monitoring system under the intelligent traffic system, and then introduced the related knowledge of the intelligent traffic monitoring system under the intelligent traffic system [7]. Brennand studied the influence of feedback information based on the cellular automata model of urban traffic. The performance of the system will be better than providing all the traffic information of the road when providing the traveler with the traffic information of part of the road. On this basis, more efficient routing strategies can be provided with less information. He demonstrated that providing only traffic information for about the first half of the road from downstream to upstream maximizes the system’s traffic capacity. He also explained these phenomena by studying the distribution patterns of vehicles and the detailed turning environment of intersections. He also provided the effect of traffic light periods [8]. In real traffic systems, information feedback has been shown to be a good way to alleviate traffic congestion. However, due to the large amount of traffic information in real systems, this process is often difficult in practice.

3. Resilient Transportation System Approach

3.1. Design Scheme of Urban Flexible Transportation System. In the urban intelligent transportation system, the control of traffic signals is the most basic control method and has the role of enforcement. The control of the signal needs to collect the traffic flow information and road condition information
of the road. It includes traffic flow and traffic density. This information can be collected by fixed monitoring nodes at intersections [9]. According to the application scenarios and characteristics of the urban intelligent transportation system, it discusses the main problems of the system in detail and gives specific solutions for each problem. Its general framework mainly includes the cooperative optimization control strategy of traffic lights, the collection and prediction of traffic flow data, the traffic guidance of autonomous vehicles, and other key issues. This section presents a general framework for an urban intelligent transportation system. Its main structure is shown in Figure 1.

As shown in Figure 1, the obtained real-time traffic flow information can be relayed to the control node at the intersection through several moving vehicle-mounted nodes. The wireless transceiver module of the control node at the intersection can receive the traffic flow information sent by each vehicle and perform data filtering processing to obtain more reliable real-time information. This real-time traffic information is used both for the control of signal lights and for autonomous traffic flow induction. It can also be used to form optimal paths for vehicles and can be used as a basis for large-scale road network timing constraints to induce task decomposition and planning [10]. Either signal control or autonomic induction is a cooperative behavior. That is, the control and induction of a traffic intersection are not the behavior of an isolated node. It uses the current traffic flow, vehicle density and queuing information of the surrounding adjacent traffic intersections, and the control input of the adjacent traffic intersections. It is necessary to carry out coordinated traffic control and autonomous vehicle guidance for the traffic in a specific area. At the same time, each intersection also needs to accept the centralized control and guidance of the urban traffic command center.

3.2. Establishment of Vehicle Sensor Network Communication Mode. Roadside access nodes are both sink nodes and gateways in this network. The vehicle sensor node transmits the collected road condition information to the roadside access node. The access node fuses the received information and sends it to the traffic management center [11]. In this model, the car is not only the main component of information perception but also the consumer of perception information. The vehicle sensor network communication mode is shown in Figure 2.

As shown in Figure 2, in the urban road condition monitoring application, each vehicle equipped with road condition sensing equipment can be used as a node in the vehicle sensor network. As the vehicle travels, the perception device is able to sample road condition information along the way [12]. At the same time, as a consumer of congestion information, the driver of each vehicle is concerned not only with the current traffic congestion at the vehicle’s location. It should also include the information on the road segments he will pass through so as to optimize the path selection. A typical architecture of an in-vehicle sensor network is shown in Figure 3.

As shown in Figure 3, in the process of traveling, in addition to constantly perceiving the traffic congestion at the location, the vehicle also continuously exchanges information with other on-board sensing nodes. The vehicle power supply system is responsible for the power supply of all modules or interfaces. The central intrusive processor collects the raw data of the sensing device. It is processed and stored in the storage device, and then the data are sent to the computer through the wireless communication module. The wireless communication module is used to realize data connection between vehicles or information exchange with roadside equipment. The on-board storage device stores various information collected by on-board sensors [13]. Combined with the characteristics of wireless sensor network networking and the actual situation of traffic flow detection, the VSN-U network model is shown in Figure 4.

As shown in Figure 4, the urban area is extensive and scattered, and the target information changes rapidly. The target information transmission distance is long and requires real-time, and it must be able to adapt to burst traffic. The roadside sensing nodes are evenly deployed along the road, and the vehicle sensing nodes are deployed on the vehicle [14].

3.3. The Principle of Classification of Risk Levels in Traffic Scenarios and the Construction of Datasets

3.3.1. Static Complexity. The static complexity is calculated according to the type, number, size, distance and other factors of the traffic objects in the scene, and the results of the object detection algorithm can reflect this information. The larger the size of the target detection frame, the larger the actual size of the target, or the closer the target is to the vehicle, the greater the potential danger.

\[
C_s(t) = \frac{\sum P(C_i) \times H_i \times W_i}{H \times W}
\]  

(1)

The number of traffic targets on the road is small and the types are single. It has a moderate distance from its own vehicle and low static complexity, making it safer to drive in this scenario [15]. In the scene of two traffic intersections, the number of targets is large, the types are complex, the distance between vehicles is short, and the complexity of the scene is relatively high. In comparison, this scenario has a higher risk of a traffic accident.

3.3.2. Dynamic Complexity. Vehicle trajectories in traffic scenes reflect dynamic order. It proposes to use the similarity of vehicle trajectories to measure this order and defines it as dynamic complexity [16]. Usually, in low-risk traffic scenarios, the direction and speed of vehicles are relatively stable, the trajectories are relatively similar, and the dynamic complexity is low. A more chaotic travel trajectory indicates a higher possibility of a traffic accident.

The one-way Hausdorff distance is a minimax function. Its calculation method is to traverse the point \( x \in A \) in the trajectory \( A \), find the point \( y \in B \) in the trajectory \( B \) closest to it and calculate the minimum distance, and then take the
Figure 1: System architecture of cooperative control and induction.

Figure 2: Schematic diagram of vehicle sensor network communication mode.
Figure 3: Block diagram of the node structure of the vehicle sensor network.

Figure 4: VSN-U network model.
maximum value of these minimum distances [17]. The specific calculation formula is as follows:

\[ H'(A, B) = \max \{ \|x, y\| \} \text{.} \]  

(2)

Among them, I and II are optional measurement methods. The one-way Hausdorff distances are not symmetrically equal; i.e., the two-way Hausdorff distance \( H(A, B) \) between trajectory \( A \) and trajectory \( B \) needs to take the maximum value of the two one-way Hausdorff distances. Its calculation formula is as follows:

\[ H(A, B) = \max \{ H'(A, B), H'(B, A) \} \text{.} \]  

(3)

Euclidean distance is a classic measure of length. It refers to the actual distance between two points in the coordinate space [18]. In the two-dimensional coordinate space, the Euclidean distance between point \((x_1, y_1)\) and point \((x_2, y_2)\) is calculated as follows:

\[ D_{\text{length}} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \text{.} \]  

(4)

Cosine distance is a calculation method to measure the similarity of directions. It can determine the similarity of the two vector directions by calculating the cosine value of the angle between the two vectors, and the cosine distance can be obtained by subtracting the cosine value from 1. In the two trajectories, their starting points are placed at the origin of the two-dimensional coordinates, then the calculation method of the cosine distance between point \((x_1, y_1)\) and point \((x_2, y_2)\) on the two trajectories is as follows:

\[ D_{\text{angle}} = 1 - \frac{x_1x_2 + y_1y_2}{\sqrt{x_1^2 + y_1^2} \times \sqrt{x_2^2 + y_2^2}} \text{.} \]  

(5)

It takes the Euclidean distance and the cosine distance, respectively, into the Hausdorff distance and normalizes it to obtain the length and angular distances. The standard deviation is calculated separately to reflect the distribution of the values, and finally, the two are summed to obtain the dynamic complexity.

\[ C_D(t) = \sqrt{\frac{\sum (H_{\text{length}}(i, t) - \bar{H}_{\text{length}}(t))^2}{n}} + \sqrt{\frac{\sum (H_{\text{angle}}(i, t) - \bar{H}_{\text{angle}}(t))^2}{n}} \text{.} \]  

(6)

Among them, \( \bar{H}_{\text{length}}(t) \) and \( \bar{H}_{\text{angle}}(t) \) are the average of the Hausdorff length distance and angular distance of all trajectories at time \( t \), and angular distance of all trajectories at time \( t \), respectively [19]. The scene complexity is divided into two parts: static complexity and dynamic complexity, and the overall complexity \( C(t) \) of the scene at time \( t \) is the weighted sum of static complexity and dynamic complexity:

\[ C(t) = a_sC_s(t) + a_dC_D(t) \text{.} \]  

(7)

Among them, \( a_s \) and \( a_d \) are the static complexity and dynamic complexity of the scene at time \( t \), respectively; \( C_s(t) \) and \( C_D(t) \) are the weights of the static complexity and dynamic complexity, respectively.

### 3.3.3. Calculation of Optical Flow

There is a basic assumption in the calculation of optical flow: the brightness is constant in a very short period of time; that is, the brightness of a pixel along a certain trajectory in each frame is unchanged [20]. According to the basic assumptions, the formula can be obtained:

\[ I(x + dx, y + dy, t + dt) = I(x, y, t) \text{.} \]  

(8)

The first-order Taylor expansion of the above formula can be obtained to obtain the following formula:

\[ I(x, y, t) + \frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt + o(d^2) = I(x, y, t) \text{.} \]  

(9)

According to the known conditions, after sorting out the above formula, the following formula can be obtained:

\[ I_xu + I_yv + I_t = 0 \text{.} \]  

(10)

Among them, the position and vector form of \( I_xu \) and \( I_yv \) are in the following formulas:

\[ \nabla \cdot V_p + I_t = 0 \text{.} \]  

(11)

Among them, \( \Delta I \) is the gradient of the luminance \( I \) at the pixel point \( P \) and is the optical flow of the pixel point \( P \).

RGB images contain rich apparent features. However, it is difficult for the network to extract effective motion features from it, and optical flow makes up for this defect [21]. It inputs the optical flow information into the neural network for training, which enables the network to perceive the relationship between the movement pattern of the traffic target and the risk of the traffic scene and improves the accuracy.

### 3.3.4. Goal-Guided Spatial Attention Module

The attention mechanism is a visual signal processing mechanism evolved by humans and some other animals in order to adapt to the living environment. When arriving in a new environment, humans generally browse the global information quickly, find the target of interest and focus on it in the follow-up observation activities. They come to obtain more detailed information on these goals and pay less attention to other useless information. Such mechanisms allow the brain to more efficiently collect useful features with limited resources. In recent years, attention mechanism has become a research hotspot in the field of neural networks and machine learning. It is widely used in advanced methods in computer vision, natural language learning, and speech recognition [22, 23].

In traffic scenarios, drivers generally focus on traffic participants on the road and various traffic signals and signs to obtain their location information, speed information, and motion information to make decisions on the next driving operation. Similarly, in the intelligent driving system, the environment perception network should also focus on the traffic targets on the road. To simulate this characteristic of drivers, an object-guided spatial attention module is designed in the video preprocessing stage. The schematic
The spatial attention matrix is calculated for each input video frame, and then the RGB image, $t \in \{1, 2, ..., T\}$ and optical flow are converted into the form of tensors. They are multiplied by the spatial attention matrix, respectively, and the inputs of the spatial flow network and the temporal flow network are obtained. The process can be expressed as follows:

$$A^S_t (P(t)) = \max \left( \rho(P(t) \in C_i) \cdot \omega(C_i) \right) \bigcup \max \left( \rho(P(t-1) \in C_i) \cdot \omega(C_i) \right).$$  

The calculation method is as follows:

$$F^S_t = I_t \odot A^S_t (P(t)), \quad F^T_t = O_t \odot A^T_t (P(t)).$$  

In the formula, $\omega$ represents the spatial attention coefficient, which is a pixel-wise coefficient calculated for each pixel. $P(t)$ represents the pixel of the $t$-th frame. $\rho(P(t) \in C_i)$ is the probability that the pixel $P(t)$ belongs to each category of objects in the object detection result (only objects related to traffic activities are considered here, such as pedestrians, cyclists, and vehicles). Since the optical flow is calculated based on two frames, the position of the object may change. For the above considerations, the spatial attention matrix of the temporal stream is the foreground union of the spatial attention matrix of the current moment and the previous moment, which is expressed as follows:

$$A^S_t (P(t)) = \max \left( \rho(P(t) \in C_i) \cdot \omega(C_i) \right).$$  

In the formula, $\omega$ represents the spatial attention coefficient, which is a pixel-wise coefficient calculated for each pixel. $P(t)$ represents the pixel of the $t$-th frame. $\rho(P(t) \in C_i)$ is the probability that the pixel $P(t)$ belongs to each category of objects in the object detection result (only objects related to traffic activities are considered here, such as pedestrians, cyclists, and vehicles). Since the optical flow is calculated based on two frames, the position of the object may change. For the above considerations, the spatial attention matrix of the temporal stream is the foreground union of the spatial attention matrix of the current moment and the previous moment, which is expressed as follows:

$$F^S_t = I_t \odot A^S_t (P(t)) \bigcup \max \left( \rho(P(t-1) \in C_i) \cdot \omega(C_i) \right).$$  

In the formula, $\omega$ represents the spatial attention coefficient, which is a pixel-wise coefficient calculated for each pixel. $P(t)$ represents the pixel of the $t$-th frame. $\rho(P(t) \in C_i)$ is the probability that the pixel $P(t)$ belongs to each category of objects in the object detection result (only objects related to traffic activities are considered here, such as pedestrians, cyclists, and vehicles). Since the optical flow is calculated based on two frames, the position of the object may change. For the above considerations, the spatial attention matrix of the temporal stream is the foreground union of the spatial attention matrix of the current moment and the previous moment, which is expressed as follows:

$$F^S_t = I_t \odot A^S_t (P(t)) \bigcup \max \left( \rho(P(t-1) \in C_i) \cdot \omega(C_i) \right).$$  

Among them, $\odot$ represents the pixel-wise multiplication. It should be noted that when multiplying, the spatial attention weights are propagated along the channel dimension. In addition, the accuracy rate ACC is also used as the overall evaluation index of the model, indicating the percentage of correctly classified samples to the total number of samples. The calculation method is as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (15)$$

The precision rate PRE represents the proportion of true cases predicted as positive cases, and the calculation formula is as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (16)$$

The recall rate REC represents the proportion of positive examples predicted to be true examples, and the calculation formula is as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (17)$$

$F_1$-score is obtained by calculating the harmonic mean of precision and recall, which can comprehensively reflect the quality of these two indicators. $F_1$-score is usually used to comprehensively evaluate the classification effect of imbalanced samples in multiclassification tasks, so it is also suitable for this task.

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (18)$$

Among them, TP represents True Positive, that is, the number of positive samples that are correctly classified. TN stands for True Negative, that is, the number of negative samples that are correctly classified. FP stands for False Positive, which is the number of negative samples that were misclassified. FN stands for False Negative, that is, the number of positive samples that are misclassified.

4. Traffic Risk Estimation Methods

4.1. Sampling Frequency Experiment. To solve the problem of information redundancy between adjacent frames, a strategy of sparse temporal sampling is adopted in the video preprocessing stage. It divides the 20-frame video into several parts and randomly selects a frame from each part to combine into a new “video.” In this subsection, experiments are designed to compare and evaluate the effect of different sampling frequencies on the experimental results. The experimental results of sampling frequency are shown in Table 1.

As shown in Table 1, in a 20-frame video, all video frames are fed into the network or a high sampling frequency is selected. Since the information between adjacent frames is very similar, the network cannot collect effective features related to traffic risk. The corresponding accuracy rates can only reach 61.11% and 62.03%. When the sampling interval is long and the sampling frequency is low, the network cannot extract enough features. The accuracy rate is only 66.67% when 2 out of 20 frames are extracted for training. It can be seen from the experimental results that when the
sampling rate is 15%–50%, the network can obtain better classification results. When choosing 4 frames out of 20, the accuracy and $F_1$-score are the highest, at 82.41% and 0.83, respectively. Considering the three factors of comprehensive accuracy, $F_1$-score, and speed, it chooses to sample 4 frames every 20 frames, and this sampling frequency can achieve the best effect. In subsequent experiments, this sampling frequency was used.

4.2. Ablation Experiment. To comprehensively evaluate whether the proposed weighted time-shift module, the goal-guided spatial attention module and the channel attention module are effective. Ablation experiments are designed, and the experimental results are presented in Table 2.

As shown in Table 2, the baseline of spatial flow is a single-frame classifier based on ResNet-50. As expected, the single-frame classifier based on 2D convolution is not designed with a temporal feature-aware structure and cannot effectively perceive the temporal information between video frames. Therefore, it performs very poorly on the risk estimation of traffic scenarios, with an accuracy rate of only 62.96%.

4.3. Comparative Experiment. Although the results of spatial flow and temporal flow are similar, they differ in their identification performance for various risk levels. False-positive samples of spatial stream networks are mainly concentrated in high-risk and accident-level scenarios. In these two scenarios, the performance of the temporal stream network is better than that of the spatial stream. This result reflects that the temporal flow network is more sensitive to dynamic features. Therefore, the two branches are proportionally fused in the backend. Finally, the best results are obtained, and the confusion matrix of traffic scene risk estimation results is shown in Table 3.

The classification results of the proposed attention-based time-shifted two-stream convolutional neural network for traffic scenes with different risk levels are shown in the confusion matrix in Table 3. This method has the best recognition effect on low-risk scenes, with an accuracy of 95.65%. The accuracy rates for medium risk and high risk were 79.17% and 80.76%, respectively. Accident-level traffic scenarios are difficult to identify in other methods, but the method achieves 77.14% accuracy. These results also demonstrate that the proposed method has a good recognition effect for scenarios with various risk levels.

In addition to the indicators used in the above experiments, the ROC curve (Receiver Operating Characteristic curve) and the P-R curve (Precision-Recall curve) are also commonly used evaluation methods in classification tasks. The ROC curve is drawn by calculating the True-Positive Rate (TPR) and False-Positive Rate (FPR) of the output results under various confidence thresholds. The P-R curve is drawn by calculating and plotting the precision and recall of the output results at various confidence thresholds. The larger the area under the curve, the better the classification effect.

### Table 1: Sampling frequency experimental results.

| Sampling frames per 20 frames | Accuracy (%) | F1-score | FPS |
|-------------------------------|--------------|----------|-----|
| 2                             | 66.67        | 0.68     | 27  |
| 3                             | 74.54        | 0.74     | 26  |
| 4                             | 82.41        | 0.83     | 25  |
| 5                             | 79.62        | 0.81     | 25  |
| 6                             | 75.46        | 0.76     | 23  |
| 8                             | 77.31        | 0.78     | 22  |
| 10                            | 72.69        | 0.72     | 20  |
| 16                            | 62.03        | 0.60     | 17  |
| 20                            | 61.11        | 0.58     | 15  |
4.4. Traffic Allocation and Route Selection of Intelligent Traffic Flow Guidance System. Most of the above research results belong to the category of static models, whether they are equilibrium models or nonequilibrium models. The traffic flow changes with time and the static model cannot describe the time-varying characteristics of the traffic flow. For some small urban traffic networks with relatively stable traffic and uncrowded traffic, it is more feasible to use a static model because the travel time of a road section is less affected by traffic. The road network in big cities is complex and changeable, and the congestion is high. Various emergencies can lead to rapid changes in road network conditions at any time, especially during rush hours. Therefore, the driving time varies significantly with the traffic flow, and the traffic conditions largely determine the driving time. The dynamic coordination of control and induction is shown in Figure 6.

As shown in Figure 6, the spatiotemporal change process of road condition information, such as the traffic flow of each road section in the road network, is the primary consideration for the traffic control and guidance of the urban road network. In addition, it is also necessary to consider how to take effective measures to ease the traffic flow as soon as possible and restore normal traffic when the urban road network throughput is too large and traffic is paralyzed. The static model of these elements is difficult to describe. In order to express this kind of internal and ever-changing traffic, it is necessary to carry out dynamic analysis, that is, to study the dynamic model. Dynamic models are divided into two categories: dynamic path models and dynamic departure models. The former considers the driver's interests, how to choose the optimal path. The latter is to consider the moment of departure, how to start at the best moment. This is a typical problem with dynamic traffic assignments.

5. Effectiveness of the Resilient Transportation System Approach

5.1. Comparison of Traffic Volume, Load Degree, and Travel Impedance Distribution of Road Sections. The implementation of the one-way traffic organization plan will significantly improve the driving conditions of the branch roads. When the service level of the branch road is higher than the service level of the parallel trunk road, part of the traffic flow will be diverted to the branch road, and other roads within its influence area will also be affected. Figure 7 shows the comparison chart of the trend of the load degree of the main road section.

Figure 7 shows the changing trend of the load degree of each arterial road section before and after the one-way traffic organization. After organizing one-way traffic, more than 50% of the road sections have reduced load. In total, 12 road sections, such as 1–5, 2–12, 24–30, 3–30, 1–7, 4–25, 3–34, 5–1, 12–2, 30–3, 7–1, and 34–3, before the implementation of the one-way traffic plan, the load degree of the road sections were all greater than 1.18. The load degree of road section 30–3 is as high as 1.65, and the congestion degree is relatively high. After the implementation of the one-way traffic plan, except for sections 1–5, 3–34, and 7–1, the load of the other 9 sections has decreased to varying degrees. It can be seen that after the organization of one-way traffic, the traffic pressure on the high-saturated thousand-road section in the region is relieved.

As shown in Figure 8, the comparison between the free impedance and the actual travel impedance before and after the implementation of one-way traffic on the main road section shows that the actual travel impedance decreases after the implementation of one-way traffic, and the distribution is relatively concentrated. The actual impedance of road sections 24–30, 3–30, 1–7, 4–25, 5–1, 6–2, 30–3, and 34–3 is obviously reduced. This is consistent with the trend that the load degree of the corresponding road section decreases significantly. The implementation of the one-way traffic plan reduces the travel time of users on the main road sections in the area, and the road traffic operation efficiency is improved.

5.2. Comparative Analysis of One-Way Traffic Optimization Schemes under Elastic Demand and Fixed Demand. According to the established model, there are 29 one-way sections under the one-way traffic organization optimization.
Figure 6: Dynamic coordination of signal control and induction in the urban intelligent transportation system.

Figure 7: Comparison chart of load degree change trend of main road sections.
scheme under flexible demand and 22 one-way sections under the fixed demand scheme. It uses the ABC algorithm to solve the available elastic demand and the optimization scheme under the fixed demand, as shown in Figure 9.

As shown in Figure 9, it is mainly developed from three aspects: the change of the average load of the road section, the detour of the vehicle, and the increase of the parking space. It compares and analyzes the optimization effect of the one-way traffic scheme under elastic demand and fixed demand traffic allocation (hereinafter referred to as the elastic demand scheme and the fixed demand scheme).

5.3. Comparison of Average Load of Road Sections. In order to compare the optimization effect of the elastic and fixed demand schemes, firstly, the influence of different one-
way traffic schemes on the congestion degree of the road network is analyzed by taking the average load degree of the road section as the index. Table 4 shows the comparison of the average load of the road sections under the elastic and fixed demand schemes.

As shown in Table 4, compared with the fixed demand, the average load of the trunk road under the flexible demand scheme has a greater reduction, which is 4% lower than that of the fixed demand scheme. At the same time, the average load of the branch has increased more, which is 4% higher than that of the fixed demand scheme. It can be seen that under the elastic demand scheme, the distribution of traffic flow in the road network is more balanced, the optimization effect of relieving traffic pressure on trunk roads and improving the utilization rate of branch roads is more significant.

The one-way traffic organization optimization model under elastic demand considers the impact of demand changes and is more in line with the actual traffic network operating conditions. The travel demand between ODs will vary with the congestion degree of the road network, and travelers are more sensitive to travel impedance. When the congestion degree of the main road gradually increases, the traveler is more inclined to choose the branch road with lower impedance. Therefore, the distribution of traffic flow under the elastic demand scheme is more balanced, and the optimization effect of the one-way traffic organization scheme is more significant.

5.4. Comparison of Bypass Indicators. The implementation of a one-way traffic organization will make some travelers unable to travel on the original route. It must find alternative paths, and detours that are too long will make it difficult for travelers to accept. Therefore, evaluating vehicle detours is an important part of evaluating one-way traffic schemes. The total detour distance OR under the elastic and fixed demand schemes, the detour distance R per vehicle, and the detour coefficient Kp are shown in Table 5.

As shown in Table 5, compared with the fixed demand, the detour coefficient and vehicle detour distance under the flexible demand scheme both increase slightly. Compared with the fixed demand scheme, the detour coefficient is increased by 0.01, and the per-vehicle detour distance is increased by about 18 m compared with the fixed demand scheme. This is mainly due to the fact that there are 29 one-way road sections under the flexible demand scheme and 22 one-way sections under the fixed demand scheme. Compared with the fixed demand scheme, the flexible demand scheme sets more one-way road segments, and accordingly, travelers need to find alternative routes to complete the original trip. Therefore, under the elastic demand scheme, the vehicle detour distance is longer.

6. Conclusion

This article focuses on the increasingly serious traffic problems in the current urban development. It adopts a one-way traffic organization, which is an effective means to make full use of existing urban traffic resources and relieve urban traffic congestion. Combined with the traffic characteristics of urban office areas, a two-level planning model for optimizing one-way traffic organization in urban office areas is established. It designs an artificial bee colony algorithm (ABC) to solve it. It starts from three aspects: the change of the average load of the road section, the detour of the vehicle, and the increase of the parking space. It compares and analyzes the optimization effect of the one-way traffic scheme under the traffic allocation of elastic demand and fixed demand. Under the scale and topology of the road network in the research area of this article, compared with the one-way traffic scheme under fixed demand, the traffic flow distribution in the road network is more balanced when considering the traffic allocation of elastic demand. The number of on-street parking spaces that can be set on the branch road is more, and the vehicle detour coefficient is slightly increased. But the increase is only 0.01, which is within the acceptable range. The one-way traffic organization scheme considering elastic demand traffic allocation has more significant optimization effects. How to use the interaction between the vehicular wireless network nodes to reduce the data flow and control the flow of roadside sensing nodes is the next problem to be studied in this article in the vehicular wireless sensor network.
Data Availability
This article does not cover data research. No data were used to support this study.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

References
[1] Z. Liu, S. Jiang, P. Zhou, and M. Li, “A participatory urban traffic monitoring system: the power of bus riders,” IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 10, pp. 2851–2864, 2017.
[2] J. Wang, M. Nguyen, and W. Yan, “A framework of event-driven traffic ticketing system,” International Journal of Digital Crime and Forensics, vol. 9, no. 1, pp. 39–50, 2017.
[3] S. G. Sağkırtios, S. K. Pantelis, I. D. Moscholios, and V. G. Vassilikis, “Call blocking probabilities in a two-link multirate loss system for Poisson traffic,” IET Networks, vol. 7, no. 4, pp. 233–241, 2018.
[4] T. Lei and Z. Hou, “Perimeter control for two-region urban traffic system based on model free adaptive predictive control with constraints,” IFAC-PapersOnLine, vol. 52, no. 6, pp. 25–30, 2019.
[5] Y.-X. Han, X.-Q. Huang, and Y. Zhang, “Traffic system operation optimization incorporating buffer size,” Aerospace Science and Technology, vol. 66, pp. 262–273, 2017.
[6] H. Yu, T. Zhen, and Y. Zhu, “Introduction to intelligent traffic monitoring system based on computer vision,” International Journal of Social Science and Education Research, vol. 2, no. 5, pp. 101–104, 2019.
[7] J. Chen, M. Li, R. Jiang, and M.-B. Hu, “Effects of the amount of feedback information on urban traffic with advanced traveler information system,” Physics Letters A, vol. 381, no. 35, pp. 2934–2938, 2017.
[8] C. A. R. L. Brennand, G. P. R. Filho, G. Maia, and F. D. L. A. Cunha, “Towards a fog-enabled intelligent transportation system to reduce traffic jam,” Sensors, vol. 19, no. 18, pp. 3916–3917, 2019.
[9] Y. Liu, X. Huang, and H. Zhang, “The assessment of traffic accident risk based on grey relational analysis and fuzzy comprehensive evaluation method,” Natural Hazards, vol. 88, no. 3, pp. 1409–1422, 2017.
[10] J. A. Fonseca, L. Estévez-Mauriz, C. Forcág, and N. Björling, “Spatial heterogeneity for environmental performance and resilient behavior in energy and transportation systems,” Computers, Environment and Urban Systems, vol. 62, pp. 136–145, 2017.
[11] W. Mutmainnah and M. Furusho, “The 4M overturned pyramid (MOP) model in maritime traffic system for safety at sea,” Navigation, vol. 191, no. 191, pp. 14–15, 2017.
[12] Z. Liu and C. Wang, “Design of traffic emergency response system based on internet of things and data mining in emergencies,” IEEE Access, vol. 7, no. 99, Article ID 113950, 2019.
[13] G. Corrarro, F. Corrarro, and E. Filippone, “Performance verification of an enhanced traffic alerting system for RPAS integration in ATM,” IFAC-PapersOnLine, vol. 51, no. 9, pp. 168–173, 2018.
[14] Y. Bhujwalla, Q. Grandemange, M. Gilson, and V. E. Laurain, “How we spend our time online: predicting network traffic using system identification,” IFAC-PapersOnLine, vol. 50, no. 1, pp. 14125–14130, 2017.
[15] A. Berrueta, P. Sanchis, and A. Ursúa, “Methodology for sizing stand-alone hybrid systems: a case study of a traffic control system,” Energy, vol. 153, pp. 870–881, 2018.
[16] S.-J. Yeh and S.-S. Jan, “Operational receiver autonomous integrity monitoring prediction system for air traffic management system,” Journal of Aircraft, vol. 54, no. 1, pp. 346–353, 2017.
[17] X. Wang, Z. Ding, X. Hu, and E. C.-H. L. B. R. Y. K. Ngai, “A city-wide real-time traffic management system: enabling crowdsensing in social internet of vehicles,” IEEE Communications Magazine, vol. 56, no. 9, pp. 19–25, 2018.
[18] Y. Ma, J. Mcgree, A. Liu, and K. P. A. Deilami, “Catchment scale assessment of risk posed by traffic generated heavy metals and polycyclic aromatic hydrocarbons,” Ecotoxicology and Environmental Safety, vol. 144, pp. 593–600, 2017.
[19] M. Ebq’ai and B. Ibrahim, “Application of multivariate statistical analysis in the pollution and health risk of traffic-related heavy metals,” Environmental Geochemistry and Health, vol. 39, no. 6, pp. 1441–1456, 2017.
[20] Q. Lian, W. Yuan, J. Yu, and X. Dang, “Traffic efficiency of post-earthquake road network in fault region retrofitted by friction core rubber bearing,” Structures, vol. 33, no. 7, pp. 54–67, 2021.
[21] Y. He, C. Sun, H. Huang, and L. M. P. C. Jiang, “Safety of micro-mobility: riders’ psychological factors and risky behaviors of cargo TTWs in China,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 80, pp. 189–202, 2021.
[22] C. Clark, P. L. Mokhtarian, G. Circella, and K. Watkins, “The role of attitudes in perceptions of bicycle facilities: a latent-class regression approach,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 77, no. 1, pp. 129–148, 2021.
[23] B. A. Morrondiello, M. R. Corbett, and E. Vander Hoeven, “Children’s street crossing performance when auditory information about traffic is lacking,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 77, no. 3, pp. 149–155, 2021.