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A Collaborative Monitoring Method for Traffic Situations under Urban Road Emergencies

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Abstract: The complex and diverse urban road traffic environments make it difficult to accurately assess road traffic situations. This paper proposes a collaborative monitoring method for urban road traffic situational assessment during emergency events. This method is applied to a monitoring network mapped by road geographic relations. When an emergency event is captured by a monitoring node in the network, road traffic situational awareness is completed by an activation function. Then, the Incidence matrix of the emergency event is constructed based on the node degree of this monitoring node. The collaborative node set and collaborative monitoring area are formed dynamically from this Incidence matrix. Finally, the AHP and EM combination weight calculation method based on Game Theory (GT-AHP-EM) is used to fuse the data of various information in the collaborative monitoring area to predict the current road traffic trend. The experiments show that the collaborative monitoring method can effectively assess road traffic conditions and enhance the accuracy of road traffic trend prediction.

Keywords: traffic situation; collaborative monitoring; game theory; situation assessment

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1. Introduction

With the complexity of urban road traffic environments, road emergencies directly threaten the regular operation of urban road traffic. The first step in many articles of research [1–5] on the global analysis of urban road traffic is to build a proper network of urban road traffic systems based on road characteristics such as road traffic facility, geographical information, traffic volume, etc., and then analyze the study subject. Researchers can add or subtract information to be displayed in this network according to their needs. It helps visualize the road traffic operation.

Road nodes are an essential part of the road network. They cooperate to monitor the traffic conditions in the target area to maintain the stable operation of the urban road traffic system. After a single road node detects a road emergency, once the monitoring target leaves the monitoring range, it cannot continuously track the target and analyze the subsequent impact of the event. Therefore, a collaborative monitoring method that can link other road nodes in the road network is needed to assess the road traffic situation in order to facilitate subsequent road protection and emergency treatment. Reducing the damage and loss of urban roads caused by emergencies is conducive to urban road traffic monitoring and early warning. There are mainly two solutions to the problem of multi-node collaborative monitoring [6]: one is that all nodes send monitoring data to the master node, and the master node conducts data fusion, analysis and judgment; the other is that each node in the network monitors and identifies the target and then sends the results of its own assessment to the master node, which completes the evaluation and decision by fusion. At present, most research on multi-node collaborative monitoring is carried out around the second idea. From the perspective of the fusion method, it mainly realizes decision and evaluation through indicators and analysis methods. In traffic situation assessment of roads in complex environments, indicators can be understood as factors to evaluate node performance, and the analysis method is mainly based on the corresponding algorithm combined with factor value and weight. Due to the particularity of risk assessment, it is impossible to obtain accurate evaluation results through only parameters; we also need to refer to experts' opinions for subjective evaluation, and reducing the emotional factors in the process of data processing is the focus of risk assessment research.

Many domestic and foreign researchers have built evaluation models based on the spectral clustering K-nearest neighbor algorithm [7], multi-objective particle swarm [8–10], continuous time dynamic Bayesian network [11–13], multi-attribute decision making [14,15] and other research methods. These methods have achieved excellent efforts in their respective fields, thus promoting the research progress of monitoring methods. Multi-attribute decision-making is still the main direction of traffic situation assessment [16–22]. In the field of road traffic, the core of the multi-attribute decision-making method is to calculate reasonable weights for different traffic attributes to assess road safety effectively. The method of combining a subjective and objective combination of assignment weights is mainly used in determining weights to determine the total weights of indicators. The subjective assignment is usually based on the Analytic Hierarchy Process (AHP) method for optimizing and improving the weight assignment [23–26]. The objective assignment is generally based on the entropy method (EM) for innovation and combination optimization [27–30]. In the process of calculating the weights, there are two points to improve. First, the subjective weight in the weighting is artificial judgment, which has intense subjectivity, so the determination of the combination coefficient is fuzzy. Second, this method is closely related to the specific algorithm, environment and network topology structure. It cannot even obtain a clear function expression, and whether it can be applied in the assessment of urban road traffic situations needs to be verified.

Thus, this paper proposes a collaborative monitoring method for urban road traffic condition assessment during emergency events. This method is divided into two stages. In the first phase, the road nodes associated with the emergency are searched in the constructed road traffic network to share the event information and start the collaborative cluster monitoring. In the second phase, the monitoring data of the cooperative node are obtained to comprehensively evaluate the road traffic situation in the event of an emergency.

2. Road Traffic Situation Assessment Model

2.1. Urban Road Monitoring Network

Aiming at the above problem of road traffic situation assessment, we construct a specific model. It can be divided into the generation of a road monitoring network, the analysis of the road collaborative monitoring area, the determination of the road traffic situation level and the formation of a collaborative monitoring model of road traffic situation assessment under emergencies.

2.1.1. Construction of the Urban Road Monitoring Network

The urban road network maps the relationship between roads, and the monitoring data of road sensors in the network can be used to objectively analyze road traffic. Therefore, building a reasonable network is a sufficient condition for road traffic situation assessment. With the server as the central node and the urban road sensor as the child node, the urban road monitoring network is constructed through the geographical location relationship between roads.

Since the main object of the urban road monitoring network diagram constructed includes the server of the application layer and the equipment sensor of the physical layer, and the intersections in the urban road traffic network are the most common intersections, this paper determines the traffic links and communication links in the network according to the road geographical location factors. It constructs the urban road monitoring network with the intersections as the main object.

The network node reflects the crossing of each urban road, and the node connectivity reflects the linkage between the roads; thus, the geographic location information of urban roads is actually indicated by the node connectivity. If there is connectivity between road i and road j, a wire connection will be made between node i and node j in the network. Similarly, it can be seen that there would not be a wire connection between node i and node j if road i and road j are not directly connected. Since our research focuses on the impact of emergencies on the roads in urban road traffic, and the possibility of multiple roads' linkage for emergency monitoring should be considered, we choose the undirected graph method in graph theory to build the monitoring network. It can remove the information that is irrelevant to this research and show the relationship between urban roads more clearly. When one of the road's monitors an emergency event, the geographic information of this road is used to identify the other roads that can engage in cluster monitoring of this emergency event and to form a collaborative monitoring area in the network for tracking the subsequent development of the emergency event on urban road traffic.

2.1.2. Collaborative Monitoring Area Based on Emergencies

The road traffic situation is closely related to node monitoring data in the network. Therefore, when conducting the traffic situation assessment for target events, a collaborative monitoring area should be determined according to the target events, and the characteristics of the road correlation between nodes should be fully considered. For the nodes distributed in the network, if these nodes can be classified and processed and the nodes associated with the target event can be arranged for collaborative monitoring, on the one hand, it is helpful to improve the accuracy of monitoring data, and on the other hand, it is beneficial to reduce the node communication energy consumption.

The model adopts the event-triggering mechanism to build a road collaborative monitoring network, as shown in Figure 1. When a road sensor detects the target event, it transforms into the event source node and uploads the target event information. The central node searches for the road node that can monitor the target event cooperatively, determines the cooperative monitoring area based on the target event, and constructs the road cooperative monitoring network based on the target event.

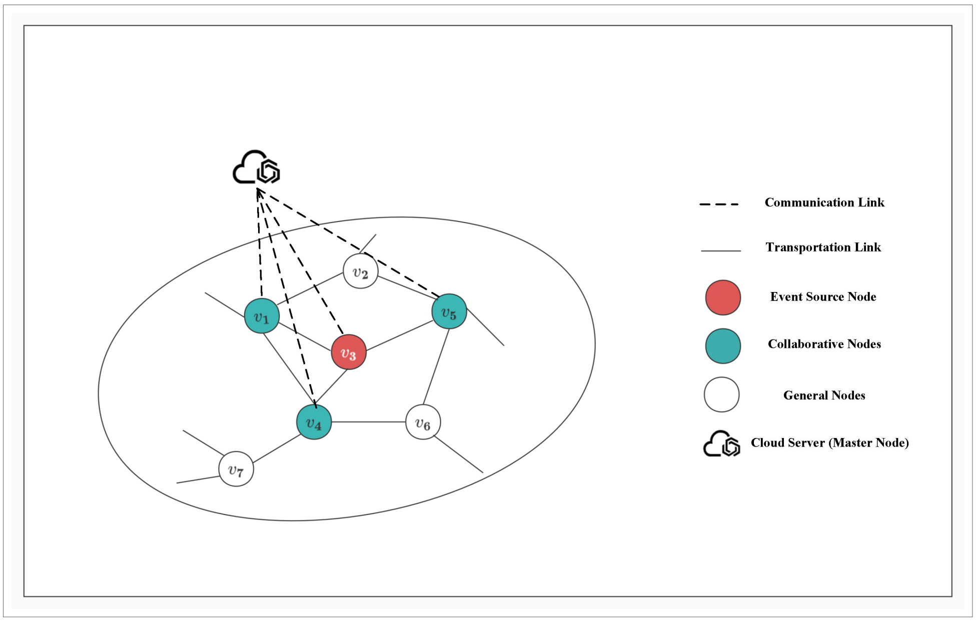

Figure 1. A road cooperative monitoring network based on emergencies.

The correlation degree in a cooperative monitoring network refers to the degree of mutual contact between roads, that is, the number of connecting edges with the road as the endpoint. The greater the correlation degree of road nodes, the more significant the impact of events on nodes and the closer the network. In the cooperative node network, the reciprocal of the node correlation degree is defined as the road correlation degree. The road correlation degree represents the basic probability that a node selects other nodes without considering road information. The urban road monitoring network takes the intersection as the main object, and the node correlation degree is 4. The above model is expanded into an undirected weighted network model, and its weight settings are shown in Figure 2.

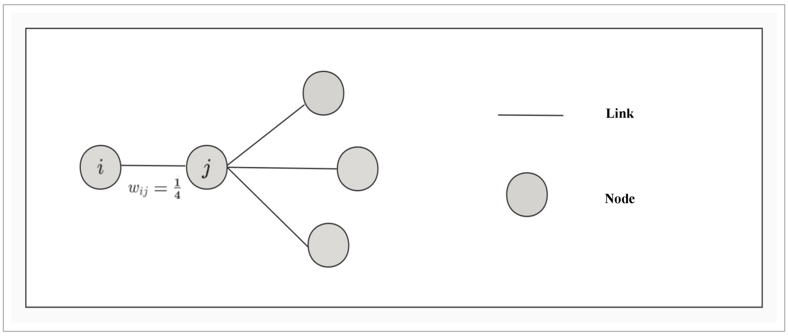

Figure 2. The setting of side weights in the road monitoring network.

In the undirected node collaborative network $G = \{V, E, W\}$, the node is expressed as $V = \{v_i \mid i \in I, I = 0, 1, 2, \ldots, N\}$, N is the number of nodes, where v_0 is Master node, v_a is a monitoring node, $a = 1, \ldots, N$; there is an edge $E = \{e_{ij} = (v_i, v_j) \mid i, j \in I\} \subseteq V \times V$ between nodes v_i and v_j. Combined with the network connectivity, the network correlation matrix $Z = \{z_{ij}\}_{N\times N}$ can be constructed; the elements z_{ij} of the network correlation matrix Z can be expressed as Equation (1), where the element z_{ij} represents the connection between nodes v_i and v_j, and n is the number of roads connected to its nodes.

$$z_{ij} = \begin{cases} 0, & (v_i, v_j) \in E \\ n(n \neq 0), & (v_i, v_j) \notin E \end{cases} \tag{1}$$

$W = \{w_{ij}\}_{N\times N}$ is the road association matrix between nodes in the network. w_{ij} represents the degree of road association between nodes v_i and v_j, and the degree of association follows a Gaussian distribution, where the element w_{ij} can be expressed as Equation (2).

$$w_{ij} = \begin{cases} 0, & \text{Node } v_i \text{ and } v_j \text{ are not associated} \\ 1/n, & \text{Node } v_i \text{ and } v_j \text{ are associated} \end{cases} \tag{2}$$

The degree of road association is related to the connection between the child nodes. Since the connection between the main node and the child nodes indicates that the main node has a communication link with the child nodes, the road association degree of the main node in the road association matrix is all 1; there is an association of road collaboration when node v_i is connected to v_j with a weight of $1/n$, where n is the association degree of node v_j; when there is no road association between nodes, the weight is 0.

2.1.3. Determination of Road Traffic Situation Level

The definition of the traffic situation is the overall road condition state and operation trend in road traffic. Traffic situation assessment is to analyze and extract many parameters, use some algorithms to evaluate and analyze the road network condition and give some guiding suggestions. In the traffic industry, the traffic situation is an indicator that can comprehensively reflect the road traffic situation. If the traffic situation can be accurately evaluated and predicted, it will be of great help to future road traffic facilitation and congestion alleviation.

In 1994, Krause proposed a situation recognition method based on fuzzy logic, combined with traffic flow and vehicle speed, and divided the traffic situation into six levels [31]. Therefore, in the evaluation methods proposed later, most scholars use the method of setting threshold ranges for grade division. The characteristic traffic parameters are used as parameters to set the threshold, such as traffic flow, average vehicle speed, delay time, road occupancy rate, etc. [32]. Therefore, the problem of evaluating and predicting the traffic situation is transformed into the issue of assessing and predicting the above parameters. Therefore, when predicting the traffic situation, the mainstream method is to predict the traffic parameters and then assess and divide by the threshold range.

However, there is no definite standard for classifying road traffic status. The urban road traffic conditions in different countries are quite different, which leads to different thresholds for each indicator for each research object, so it is not easy to divide the situation level by a specific indicator. The United States divides the traffic situation into grades through some traffic service indicators and quantifies the degree of congestion according to the indicators [33]. Germany divides the road traffic situation into five stages through road traffic flow density indicators [34]. Japan, through the analysis of traffic flow, identifies three levels of traffic service. New Zealand assesses traffic congestion levels by quantifying travel time as a congestion index. In China, the Ministry of Public Security uses the average travel time of road vehicles as an indicator to reflect the degree of traffic congestion on the road network [35]. It divides the degree of congestion into four levels.

Given the existing traffic congestion and posture classification levels, this paper completes the classification of traffic posture according to the traffic congestion level table in GB\T 33171-2016 Evaluation Specification for Urban Traffic Operation Condition (hereafter referred to as the evaluation specification). It classifies the urban road traffic posture level into five levels: unobstructed state, slightly unobstructed state, mild congestion, moderate congestion and severe congestion. Detailed traffic situation levels are described in Table 1.

Table 1. Road traffic situation level description.

Traffic Situation Level	Situation Level Description
unobstructed state	When in an unobstructed state, vehicles are widely spaced and traffic moves in an orderly manner, without interference from road events. Traffic managers do not need to manually direct traffic on city roads, and a high level of traffic safety and efficiency can be achieved.
slightly unobstructed state	When it is in a slightly unobstructed state relative to the unobstructed state, the number of vehicles on that city road increases, but it does not cause congestion. The traffic order is good, and if a road incident occurs, it will not cause disorder in the city road traffic. Traffic efficiency is at a high level at this time.
mild congestion	When in mild congestion, the traffic road is sensitive to sudden disruptions and affected by emergencies. When disturbed, the road traffic is less efficient. At this time, the normal operation of traffic can be ensured with the intervention of traffic managers.
moderate congestion	In the state of moderate congestion, the traffic road is more sensitive to the interference of emergencies and more affected by emergencies. When disturbed, road traffic is inefficient. As the complexity of urban roads increases, the chance of conflicts between vehicles increases, and most vehicles are delayed at intersections, resulting in low traffic efficiency. At this time, the traffic operation can be maintained under the intervention of the traffic manager.
severe congestion	In the state of severe congestion, the traffic road is very sensitive to the disturbance of emergencies, and it is easy to produce great fluctuations. When disturbed, most vehicles will be greatly affected, and the road traffic efficiency is very low. Urban roads are becoming more complex. At this time, the traffic manager needs to arrange multiple traffic departments to conduct traffic dredging and maintain traffic order.

2.1.4. Collaborative Monitoring Model of the Road Traffic Situation

Nodes in the urban road monitoring network detect emergencies. In order to analyze the impact of such emergencies on the road traffic of the road network, a collaborative monitoring model of road traffic situation under emergencies is built, as shown in Figure 3. This model can not only identify the road traffic state, but also predict the future traffic trend of the road to a certain extent.

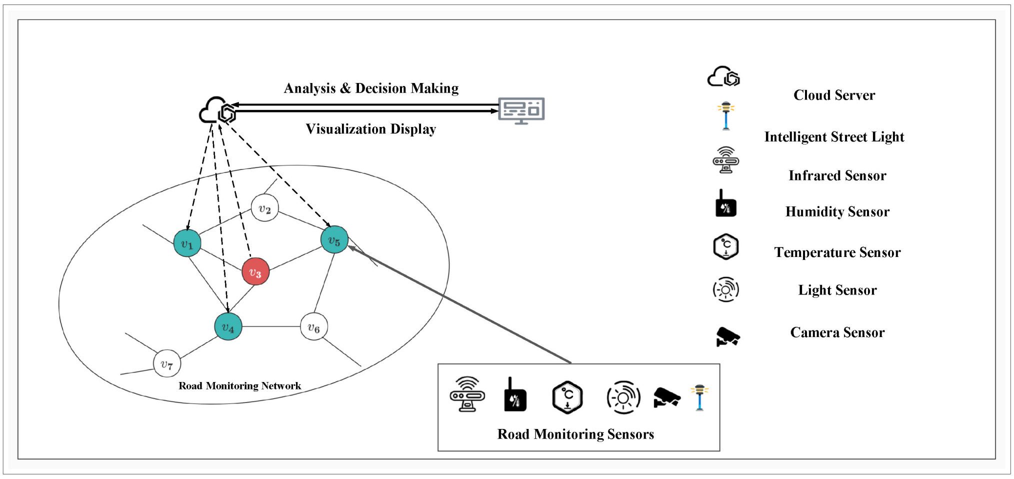

Figure 3. The road traffic situation cooperative monitoring model under emergency.

In the urban road monitoring network, the event source node v_i monitors the target event and uploads the target event information set $A = [a_1, a_2, a_3, \ldots, a_n]$. In the target event information set A, a_1 is the id information of the event source node, and $a_2 - a_n$ are the monitored target event data, such as event type, target vehicle license plate, vehicle speed, driving direction, etc.

The master node searches and communicates with collaborative nodes that can monitor the same target event according to the road correlation and obtains the monitoring data of each cooperative node. The monitoring data of each cooperative node is recorded as the cooperative node monitoring dataset $D = \{M_j \mid j \in I, I = 0, 1, 2, \ldots, N\}$ of the event source node. N is the number of nodes, where M_0 represents the monitoring information of the master node, and the default is 0; $M_a(a = 1, \ldots, N)$ is the data information of the monitoring node. Assuming that node v_j is the road coordination node of the target event, node v_j will upload the monitoring data $M_j = \left[m_j, m_j^1, m_j^2, \ldots, m_j^M\right]$, where m_j is the road, after receiving the server request. The id information of the cooperative node, $m_j^1 - m_j^M$, is the monitored road data. If the node v_j is the master node or a non-road cooperative node, the monitoring data M_j uploaded by the node v_j default to a matrix of all 0. The monitoring data M_j are expressed as Equation (3).

$$M_j = \begin{cases} \left[m_j, m_j^1, \ldots, m_j^M\right], & v_j \text{ is the road cooperative node} \\ [[0, 0, \ldots, 0], & v_j \text{ is the road non-cooperative node or master node } v_0 \end{cases} \quad (3)$$

The main node fuses the monitoring information and data according to the cooperative node monitoring dataset D, builds the collaborative road traffic situation monitoring model, analyzes and predicts the road traffic state and traffic trend, respectively, and completes the road traffic situation assessment.

2.2. *Traffic Situation Assessment Indicator Analysis*

Traffic situation assessment is divided into two steps: the first is road traffic situation awareness, and the second is road traffic situation prediction. Therefore, the analysis of road traffic situation indicators need to be analyzed separately; one is the selection of indicators for road traffic situation perception, and the other is to construct multiple indicators for road traffic situation prediction into a system of indicators. The relevance of these indicators to urban road emergencies is also discussed in this section.

2.2.1. Traffic Situational Awareness Indicator Analysis

Traffic flow data are the basis of traffic dynamics prediction problems, which can be divided into two major categories: static data and dynamic data. Static traffic data mainly contain data such as the name of the area to which the road section belongs, road network structure, road section direction, road section number and road section length, which can be used to describe the topology of the road network, while dynamic traffic data mainly contain the delay time ratio, free flow speed, average travel speed, traffic flow, etc., which are indicators that can be used to evaluate the road section traffic condition.

(1) Traffic flow

Traffic flow is the number of vehicles passing through the monitored road cross-section range per unit of time, which can be currently calculated from the monitoring data of the surveillance cameras at the intersection, as shown in Equation (4).

$$Q = \frac{N_{\text{vehicle}}}{\tau} \tag{4}$$

where Q is the unit traffic flow, the unit is vehicle per hour (pcu/h), pcu (Passenger Car Unit) represents the number of vehicular traffic; N_{vehicle} is the traffic flow, and the unit is vehicle (pcu); τ is the time interval, the unit is hour (h), usually take 15 min (0.25 h) as the time interval, and take the monitoring value within this range as the calculation data. In the case of little interference from external factors, the traffic flow usually presents a periodicity. That is, the traffic flow trend of the same road section is similar every day, every week and every month.

(2) Average travel speed

Traffic speed is divided into instantaneous speed and average speed, where instantaneous speed is the instantaneous speed of a vehicle passing through the observed section of the roadway. Furthermore, the average travel speed is the ratio of the total distance and total time of all vehicles passing through the area. The calculation method is shown in Equation (5).

$$v_{ab} = \frac{\sum_{c=1}^{x} L_{abc}}{\sum_{c=1}^{x} t_{abc}} \tag{5}$$

where v_{ab} is the average travel speed of the bth section in a time of length a, and the unit is kilometers per hour (km/h); L_{abc} is the distance traveled by the cth vehicle in the bth road section at time a, and the unit is kilometers (km); t_{abc} is the time required for the cth vehicle to pass the bth road section in time a, and the unit is hour (h); x is the number of observed vehicles.

There are many other traffic data indicators, such as delay time ratio, congestion length, traffic density, etc. However, under the condition of existing equipment, traffic flow is relatively easier to collect, and in the actual scenario, these data are also more intuitive to show the road condition, so this paper selects traffic flow as the input data for road traffic status identification.

2.2.2. Construction of the Traffic Situation Prediction Indicators System

Based on the principle of systemic and reliability of index design, the road traffic situation under emergency events is comprehensively evaluated from three aspects: road factors, natural factors and human factors. Firstly, the hierarchy is constructed by dividing the objective layer, criterion layer and indicator layer according to the decision objective, decision criterion and decision object. The constructed hierarchical structure model of road traffic situation impact under emergencies is shown in Figure 4, including three primary indicators of road impact, natural impact and human impact and ten secondary indicators such as road length, one-way road width and traffic lights. According to the hierarchical structure diagram, the assessment index system of the impact of the emergency event on the road traffic situation is constructed.

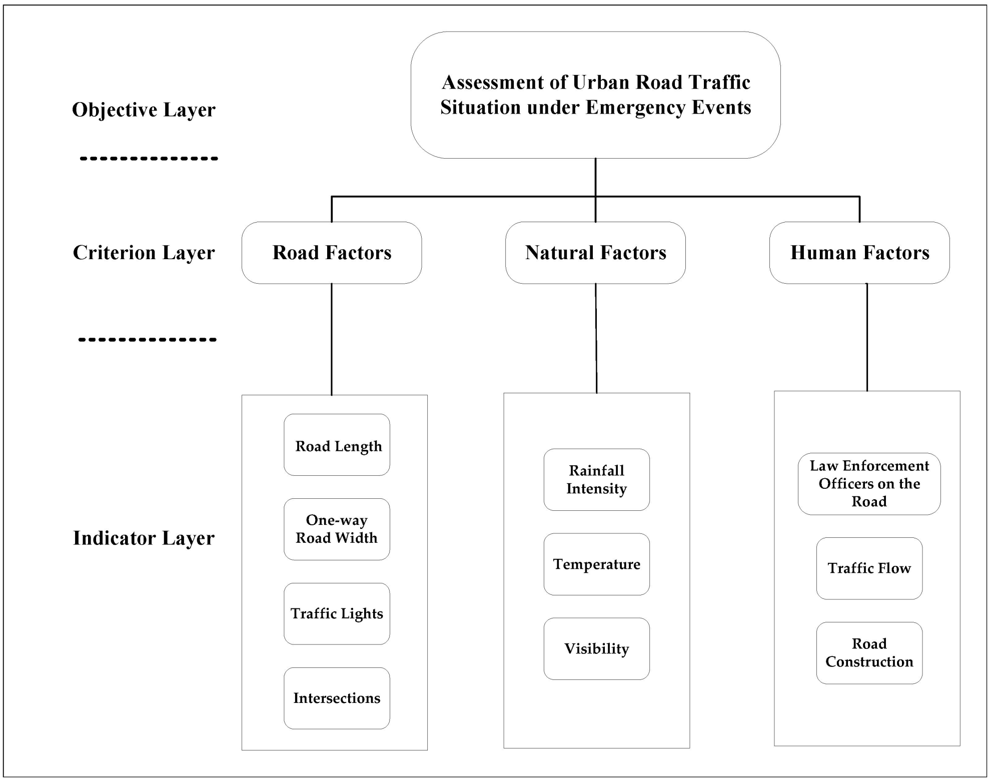

Figure 4. The hierarchical model for urban road traffic situation assessment during emergencies.

(1) Road factors U_1.

The road is a basic element of road traffic. Its design should not only meet the function of vehicle traffic, but also minimize the urban road emergencies caused by the structural design. Road geometric feature, special road section and traffic facility are all factors that affect the emergencies, which all constitute road factors.

Road geometric feature is the design part of the road. It mainly describes the road cross-section. Its indicators include road length, one-way road width, shoulder width, road median interval, etc. Special road sections in urban roads mainly refer to intersections, tunnels and other special structure sections included. They will cause visual errors to the vehicle drivers and thus increase the probability of emergencies. Setting traffic facilities is a way to manage the road. It will not only reduce the probability of road emergencies, but also help traffic management personnel to deal with emergencies quickly. A common traffic safety facility is the traffic light. This paper selects the common indicators of road length, one-way road width, traffic lights and intersections as road factor indicators.

(2) Natural factors U_2.

The natural environment includes two aspects: climatic conditions and ecological landscape. For urban road networks, climatic conditions cover the weather changes in the road environment, such as rain, snowfall, freezing, fog, etc.; ecological landscape covers the natural landscape changes around the road, such as illumination, visibility, buildings, etc., and also includes factors such as landscape singularity and landscape visual attractiveness. These conditions thus affect the road traffic status. Its main influencing factors are rainfall intensity, temperature and visibility.

(3) Human factors U_3.

Human factors are the key determinants of urban road emergencies. Human factors affect road traffic resulting in an increased probability of emergencies. It mainly includes road capacity, road construction and road enforcement. Road capacity is the ability of road facilities to divert traffic flow. It determines the current traffic operation of the road. When it is easier to relieve the traffic pressure on the road, the probability of emergencies is lower. Road construction may occupy and close some lanes of the current roadway. This can interfere with the overall traffic flow, causing a reduction in traffic capacity. Road enforcement provides more detailed traffic management on the road. Once there is a tendency of emergencies, priority treatment becomes a focus, so as to quickly protect the road to restore road traffic and maintain the normal operation of the road. Its main influencing factors are road enforcement officers, traffic flow and road construction and maintenance.

In summary, the indicator system for assessing the road traffic situation under emergencies is shown in Table 2. Finally, the set of constructed indicators is $U = (U_1, U_2, U_3)$.

Table 2. The indicator system for assessing road traffic situation under emergencies.

Target Layer	Guideline Layer	Indicator Layer
Road traffic situation assessment under emergencies V	Road Factors U_1	road length U_{11}/km
		one-way road width U_{12}/m
		traffic lights U_{13}
		intersections U_{14}
	Natural Factors U_2	rainfall intensity $U_{21}/(\text{mm}\cdot\text{min}^{-1})$
		temperature U_{22}/(°C)
		visibility U_{23}/m
	Human Factors U_3	law enforcement officers U_{31}
		traffic flow $U_{32}/(\text{Vehicles}\cdot\text{min}^{-1})$
		road section construction U_{33}

2.2.3. Analysis of Traffic Situation Prediction Indicators

Predicting the urban road traffic situation under emergencies is essentially to study and analyze the impact of emergencies on urban roads. It will be considered comprehensively according to the traffic situation prediction indicators. Therefore, we need to first analyze the correlation between traffic situation prediction indicators and urban road emergencies and then predict the urban road traffic situation under emergencies according to this correlation.

The number of urban road emergencies satisfies the following parameter characteristics:

(1) The values are non-negative integers;
(2) The probability distribution is discrete;
(3) The occurrence of emergencies are independent of each other.

It can be seen that the parameter characteristics of the number of urban road emergencies are discrete and independent and similar to the characteristics of the Poisson distribution; therefore, this paper considers the Poisson regression model to analyze the correlation between the road traffic situation prediction indicators and urban road emergencies.

Considering that "urban road emergencies" a random event Y, Poisson distribution can be used to describe the number of random events Y within a unit of time, which is the number of urban road emergencies. The Poisson distribution is used to describe the distribution of the number of urban road emergencies between the road nodes within a unit of time, and its probability function can be written as Equation (6).

$$P(Y = y_i) = \frac{\lambda_i^{y_i}}{\Gamma(y_i + 1)} e^{-\lambda_i}, y_i = 0, 1, 2, 3, \ldots; i = 1, 2, 3, \ldots, n \quad (6)$$

where y_i is the number of accidents at the ith road node, λ_i is the Poisson parameter and satisfies $E(Y) = \mu = \lambda_i$, $Var(Y)$=$\sigma^2 = \lambda_i$, μ is the expectation parameter and σ^2 is the variance parameter.

Assuming that μ_i is the mean value of Y_i, the density function of the Poisson model can be written from Equation (6). The expression is shown in Equation (7).

$$P(Y_i = y_i \mid \mu_i) = \frac{\mu_i^{y_i}}{\Gamma(y_i + 1)} e^{-\mu_i}, y_i = 0, 1, 2, 3, \ldots; i = 1, 2, 3, \ldots, n \tag{7}$$

where μ_i represents the regression model.

$$h(\mu_i) = \sum_{i=1,j=0}^{n,m} x_{ij}\beta_j = x_i^T \beta \tag{8}$$

where $\beta = (\beta_0, \beta_1, \beta_2, \ldots, \beta_m)^T$ is the $m + 1$ dimensional regression coefficient to be estimated, $x_i^T = (x_{i0}, x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im})$ is the set of covariates, x_i^T is the predicted road traffic situation at the ith road node and $x_{i0} = 1$; $h(\bullet)$ is the linkage function.

It is usually taken as $h(x) = \log(x)$, as shown in Equation (9).

$$\mu_i = \exp(x_i^T \beta) \tag{9}$$

The matrix of Equation (8) can be expressed as Equation (10).

$$h(\mu) = x^T \beta \tag{10}$$

where $x^T = \begin{bmatrix} 1 & x_{11} & x_{12} & \ldots & x_{1m} \\ 1 & x_{21} & x_{21} & \ldots & x_{2m} \\ 1 & x_{31} & x_{32} & \ldots & x_{3m} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & x_{n1} & x_{n1} & \ldots & x_{nn} \end{bmatrix}$ is the Design Matrix, $\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \ldots \\ \beta_n \end{bmatrix}$.

The Poisson regression model applied to the analysis of the association between emergencies and urban roads consists of a combination of Equations (7) and (9).

After establishing the regression model, the regression model needs to be tested. The degree of matching between the predicted indicators of road traffic situation and the sample data is checked to determine whether the regression model can effectively explain the association between urban road emergencies and the indicators, and if the results of the model have high consistency with the sample data, the established model can be considered to have high reliability. In this paper, the regression model is evaluated from two aspects: χ^2 statistical test and goodness-of-fit test.

Usually, the statistical significance of an estimated regression model is evaluated by a likelihood ratio test. The likelihood ratio statistic approximately obeys the χ^2 distribution, and the χ^2 statistic of the regression model is shown in Equation (11).

$$\chi^2 = 2LL - 2LL_0 \tag{11}$$

where LL is the natural logarithm of the estimated maximum likelihood of the regression model; LL_0 is the natural logarithm of the maximum likelihood of the null hypothesis model. After calculating the χ^2 statistic of the regression model, the significant level of the regression model can be obtained by checking the χ^2 distribution table.

The Akaike Information Criteria (AIC) statistic and the Bayesian Schwartz Criteria (BIC) statistic are the commonly used goodness-of-fit tests. The smaller the value of the AIC statistic, the better the fit of the model. Similarly, the smaller the value of the BIC statistic, the better the fit of the model. The expressions for AIC and BIC are shown, respectively, in Equations (12) and (13).

$$AIC = -2LL + 2m \tag{12}$$

$$BIC = -2LL + m\ln(n) \tag{13}$$

where LL is the natural logarithm of the estimated maximum likelihood value of the regression model, m is the number of estimated parameters in the regression model and n is the number of data samples.

2.3. Road Traffic Situation Assessment

The collaborative monitoring method proposed in this paper is an approach to assess the urban road traffic situation under emergencies. This approach accomplishes two parts of the calculation: one is road traffic situation awareness, and the other is the road traffic situation prediction. It provides data support for road traffic diversion and management and relieves road pressure.

2.3.1. Road Traffic Situational Awareness Calculation

The problem of road traffic situational awareness belongs to the problem of quantitative indicators. Road traffic situational awareness is not yet delineated with clear boundaries, and it is difficult to to identify and classify the corresponding situational level directly [36]. Therefore, it is necessary to explore the intrinsic connection of traffic data and to cluster it. Through the determination of the selected traffic situation index value changes, finding the appropriate mathematical function to calculate the five different interval values, the analysis of the five interval situation values can determine the corresponding situation level, and you can objectively identify the road traffic situation.

In this paper, traffic flow is selected for the traffic situation awareness indicator, which is calculated using the road traffic state identification method. Finally, it corresponds to the situation level determined in the Evaluation Specification for comparison.

2.3.2. Road Traffic Trend Prediction Calculation

Road traffic trend prediction is actually the fusion of monitoring data from road sensors to calculate a score to determine the degree of traffic trends affected by road emergencies. The weights assigned to the various monitoring indicators affect the final calculation results.

This method is characterized by its data input diversity and indicator assignment method comprehensively.

The diversity of data input will make the final results more comprehensive and reliable. It is mainly reflected in the types of monitoring indicators and monitoring targets. In the trend prediction, the data of multiple indicators are fused and calculated. The indicators associated with urban road emergencies are selected from three factors: road factors, natural factors and human factors for analysis; the monitoring targets are used for multiple urban road nodes. When the emergency is recognized by the event source node, the collaborative nodes are searched for in the road network, and the collaborative nodes can help to monitor this emergency, just like the UAV cluster monitoring tracks the impact generated by the emergency.

In this paper, the subjective and objective assignment methods based on game theory are used for assignment. The two indicator assignment methods are combined and considered together to reconcile the contradiction between subjective and objective weights. The indicator weights $W = \{w_1, w_2, \ldots, w_M\}$ can be combined with the collaborative node monitoring dataset D to weigh the road situation assessment indicators and calculate the corresponding road traffic trend value $F = \{f_1, f_2, \ldots, f_N\}$ in order to complete the road traffic trend prediction. M is the number of traffic risk assessment indicators, and N is the number of collaborative nodes.

3. Collaborative Monitoring Algorithms for Situational Assessment

3.1. Traffic Situational Awareness Approach

The use of metrics evaluation has become a trend in various fields. In traffic situational awareness, there have been various evaluation approaches based on the numerical changes in the acquired traffic flow, differences in road conditions and the amount of data. Some quantify parameters such as traffic speed and traffic flow by the fuzzy comprehensive evaluation method and then perform multi-level analysis; there are also traffic situation level conversions by calculating delay time ratio, congestion mileage and travel time, and such methods are commonly used for traffic situation sensing.

Traffic flow is less often used as traffic data in evaluation specifications, and a frequent traffic parameter is road space occupancy to assess the traffic situation level. There is no approach to calculating traffic dynamics directly from the traffic flow. Therefore, in the collaborative monitoring approach proposed in this paper, the traffic flow is used to determine its corresponding situation level. First, there is a relationship between traffic flow and congestion state of a road section as follows: (1) When the traffic flow is shallow, the road is very unobstructed; when the traffic flow is very high, the roadway is very congested. (2) Furthermore, the congestion state from open to congested increases rapidly with the increase in traffic flow. (3) The closer the data are to both ends, the lower the change in congestion level.

The mathematical properties of the Sigmoid function can link road traffic flow and traffic situational awareness. The Sigmoid function has three features: (1) the value domain is between $[0, 1]$; (2) the slope of the function tends to 0 when the definition domain tends to $+\infty$ or $-\infty$; (3) the function is insensitive to the horizontal axis coordinates when they exceed a specific value. The function is shown in Equation (14).

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{14}$$

The *Sigmoid* function is basically matched with the relationship between traffic flow and traffic congestion state, so the *Sigmoid* function is chosen to calculate the traffic situation level of traffic flow in this paper. The formula for calculating the traffic situation level L is shown in Equation (15).

$$L = 5 \times \text{Sigmoid}\left(\frac{10 \times F_{\text{obtain}}}{F_{\max}} - 5\right) \tag{15}$$

where F_{obtain} is the obtained traffic flow parameter, and $F_{\max}$ is the maximum traffic flow counted in the dataset. The result range of *Sigmoid* is $[0, 1]$. For the purpose of visual analysis, the result is expanded by a factor of 5 corresponding to the range of 5 situation levels to obtain the traffic situation level L.

3.2. Collaborative Traffic Trend Prediction Approach

3.2.1. Monitoring Data Pre-Processing

Assuming that the road traffic situation is assessed for M indicators in the road network under an emergency event, the monitoring data of different indicators of each road need to be dimensioned and normalized to objectively reflect the correspondence between the actual value of the indicators and the evaluation value of the indicators. Since the measurement standards of each indicator are different, it is necessary to De-dimensionalize and normalize the data of each indicator to meet the consistency and comparability among different attributes of indicators. The d_{ij} in the original dataset D means the jth indicator value of road node v_i. The positive indicator refers to the following: the larger the value of d_{ij}, the better the evaluation. Additionally, the positive indicator is also called the benefit-oriented indicator or the extremely large indicator. It is calculated as shown in Equation (16).

$$d_{ij}^{*+} = \frac{d_{ij} - \min d_{ij}}{\max d_{ij} - \min_{ij}} \tag{16}$$

The smaller the value of d_{ij}, the better the evaluation of the class of indicators is a negative indicator. It is calculated as shown in Equation (17).

$$d_{ij}^{*-} = \frac{\max_{ij} - d_{ij}}{\max_{ij} - \min_{ij}} \tag{17}$$

Finally, all indicators after processing are in the range of 0-1. The normalized dataset D^* after collation is shown in Equation (18).

$$D^* = \begin{bmatrix} d_{11}^* & \cdots & d_{1M}^* \\ d_{21}^* & \cdots & d_{2M}^* \\ \vdots & \ddots & \vdots \\ d_{N1}^* & \cdots & d_{NM}^* \end{bmatrix}_{N\times M} \tag{18}$$

3.2.2. Monitoring Indicator Weight Calculation

Game theory is an essential sub-discipline of operations research, which mainly studies the interaction between competing things and analyzes the rational behavior of multiple decision makers and their decision equilibrium when they interact with each other. This requires the parties to find an equilibrium combination that maximizes their common interests, i.e., requires the combination of weights and the minimization of the deviation between the weights [37,38], and the larger deviation produces a "compromise". The game theory-based portfolio assignment method takes the Nash equilibrium as the goal, coordinates the conflict between subjective and objective weights and finds the agreement and compromise between them, which is an integrated process of mutual comparison and mutual coordination. The method can reduce the subjective arbitrariness and also fully consider the influence of objective data to a certain extent to improve the scientific rationality of the assignment.

The AHP and EM combination weight calculation method based on Game Theory (GT-AHP-EM) uses two assignment methods to calculate the weights and then performs a secondary weighting to obtain the final weights. The AHP method was used for the subjective assignment part, and the EM method was used for the objective assignment.

The Analytic Hierarchy Process (AHP) is a multi-program decision-making method proposed by Professor T. L. Saaty, an American operations researcher. It can solve complex decision problems with multiple objectives, criteria, elements and levels. The method [39] decomposes the decision problem into numerous levels of objectives, criteria and scenarios for evaluating decisions and quantifies and correlates the relevant elements. Usually, two and two influence factors are compared [40], and the judgment matrix is constructed using the 1–9 scale method to synthesize the weight of the intrinsic influence between factors.

The entropy method (EM) is a mathematical method that can calculate the dispersion of indicators. It derives indicator weights from the amount of information provided by the indicator. If the influence of the indicator on the evaluation results is more substantial, it means that the variability among the indicators is greater. Therefore, the weights can be calculated according to the variability in indicators to provide theoretical support for comprehensive evaluation.

In this paper, the GT-AHP-EM method can not only consider the inherent information among indicators, but also reduce the one-sidedness of the single assignment method. This method improves the rationality of indicator assignment in the following steps [41].

Step 1: Calculation of weights using the AHP method.

The construction of judgment matrix $B = \begin{bmatrix} b_{11} & \cdots & b_{1M} \\ \vdots & \ddots & \vdots \\ b_{M1} & \cdots & b_{MM} \end{bmatrix}$ is carried out according to the indicator set U, where b_{ij} shows the importance of the ith indicator relative to the jth indicator in the indicator set U. Then, we determine the maximum eigenvalue $\lambda_{\max}$ and the normalized eigenvector W_1 of the judgment matrix B. In this paper, the arithmetic average method is used to calculate the maximum eigenvalues of the judgment matrix and its corresponding eigenvectors. The calculation of this method is shown in Equations (19) and (20).

$$w_{1i} = \frac{1}{M}\sum_{j=1}^{M}\frac{b_{ij}}{\sum_{k=1}^{M} b_{kj}}, (i = 1,2,\ldots,M) \tag{19}$$

$$\lambda_{\max} = \sum_{i=1}^{M}\frac{(Bw)_i}{Mw_{1i}} \tag{20}$$

The Consistency Ratio (CR) is used as a comprehensive indicator to ensure average randomness and consistency. If $CR < 0.1$, the consistency of judgment-matrix is well; if $CR > 0.1$, the judgment matrix should be reconstructed. The consistency test is calculated as shown in Equations (21) and (22).

$$CI = \frac{\lambda_{\max} - M}{M - 1} \tag{21}$$

$$CR = \frac{CI}{RI} \tag{22}$$

where CI is the consistency indicator, CR is the consistency ratio and RI is the average randomness indicator. In Table 3, 1000 simulations of Satty obtained random consistency indicator RI values are shown, and the RI values can be known by checking this table.

Table 3. Table of Random Consistency Indicator RI Values.

Orders n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.54	1.56

The final indicator weight based on the AHP method is obtained as $W_1 = (w_{11}, w_{12}, \ldots, w_{1M})^T$.

Step 2: Calculation of weights using the EM method.

The d^*_{ij} of the normalized dataset D^* obtained by data pre-processing in Section 3.2.1 is used to calculate the entropy value e_j of each indicator. It is shown in Equation (23).

$$e_j = -k\sum_{i=1}^{N} d^*_{ij}\ln(p_{ij}) \tag{23}$$

where d^*_{ij} is the ith road and the jth indicator value $(i = 1,2,\ldots,N; j = 1,2,\ldots,M)$, N is the number of road and M is the number of indicators. k is a constant related to N, $k = \frac{1}{\ln N}$. d^*_{ij} satisfies $\sum_{j=1}^{N} d^*_{ij} = 1$, and when $d^*_{ij} = 0$, let $p_{ij}\ln\left(d^*_{ij}\right) = 0$.

Calculate the coefficient of variation g_j and the objective weight w_{2j} of the jth indicator, which are shown in Equations (24) and (25).

$$g_j = 1 - e_j \tag{24}$$

$$w_{2j} = \frac{g_j}{\sum_{i=1}^{N} g_i}, (i = 1, 2, \ldots, N) \tag{25}$$

The final indicator weight based on the EM method is obtained as $W_2 = (w_{21}, w_{22}, \ldots, w_{2M})^T$.

Step 3: Calculate the combination coefficient of the multiple assignment methods.

The weights $W_1 = (w_{11}, w_{12}, \ldots, w_{1M})^T$ calculated by the AHP method and the weights $W_2 = (w_{21}, w_{22}, \ldots, w_{2M})^T$ calculated by the EM method form the basic weight set $W = \{W_1, W_2\}$; the two indicator weights W_1 and W_2 can be regarded as the two sides of the game, and the optimal combination of weights can be considered as the two sides of the game reaching the equilibrium state. The method is shown in Equation (26).

$$W = \sum_{k=1}^{2} \alpha_k W_k^T, \alpha_k > 0 \tag{26}$$

where α_k is the combination coefficient of the assignment method, and W_k^T is a set of assignment vectors of the weight set. $\alpha = \{\alpha_1, \alpha_2\}$ is the linear combination coefficient, so Equation (18) is equivalent to Equation (27).

$$W = \alpha_1 W_1^T + \alpha_2 W_2^T \tag{27}$$

According to the theory of the game assembly model, the objective is to optimize the two linear combination coefficients α_1 and α_2 in Equation (18) by minimizing the deviation of W and W_k to obtain the optimal weight W^*. The Game Model is shown in Equation (28).

$$\begin{gathered} \min \left\| \sum_{k=1}^{2} \alpha_k W_k^T - W_k \right\|_2 \\ \text{s.t. } \alpha_1 + \alpha_2 = 1, \quad \alpha_1, \alpha_2 \geq 0 \end{gathered} \tag{28}$$

According to the matrix differentiation property, the expression of Equation (27) is converted into a system of linear differential equations under the optimal first-order derivative condition, and the result is shown in Equation (29).

$$\begin{bmatrix} W_1 {W_1}^T & W_1 W_2^T \\ W_2 W_1^T & W_2 W_2^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} W_1 {W_1}^T \\ W_2 W_2^T \end{bmatrix} \tag{29}$$

The optimized combination coefficients α_1 and α_2 calculated by Equation (20) are normalized as shown in Equation (30).

$$\alpha_k^* = \frac{\alpha_k}{\sum_{k=1}^{m} \alpha_k}, (k = 1, 2) \tag{30}$$

The combination coefficients of the two assignment methods in this paper are $\alpha_1^* = \frac{|\alpha_1|}{|\alpha_1| + |\alpha_2|}$ and $\alpha_2^* = \frac{|\alpha_2|}{|\alpha_1| + |\alpha_2|}$, respectively.

Step 4: Calculation of the final weights.

The combination coefficients are weighted to obtain the combined weight W^*, as shown in Equation (31).

$$W^* = \sum_{k=1}^{2} a_k^* w_k^T = \begin{bmatrix} w_1^* \\ w_2^* \\ \vdots \\ w_M^* \end{bmatrix}_{M \times 1} \tag{31}$$

3.2.3. Traffic Trend Prediction

To facilitate visualization of the evaluation results, the standardized data matrix D^* and the combined weight of indicators W^* are weighted to obtain the road traffic trend value F, as shown in Equation (32).

$$F = D^*W^* = \begin{bmatrix} d_{11}^* & \cdots & d_{1M}^* \\ d_{21}^* & \cdots & d_{2M}^* \\ \vdots & \ddots & \vdots \\ d_{N1}^* & \cdots & d_{NM}^* \end{bmatrix}_{N\times M} \begin{bmatrix} w_1^* \\ w_2^* \\ \vdots \\ w_M^* \end{bmatrix}_{M\times 1} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix}_{N\times 1} \tag{32}$$

Normalize the traffic trend value F and construct the normalized road traffic trend value $F^* = \begin{bmatrix} f_1^* \\ f_2{}^* \\ \vdots \\ f_N{}^* \end{bmatrix}_{N\times 1}$ as shown in Equation (33).

$$f_j^* = \frac{f_j}{\sum_{j=1}^{N} f_j} \tag{33}$$

3.3. Evaluation Indicators for Traffic Trend Prediction

In this paper, the road traffic trend prediction results are mainly analyzed using *Accuracy*, *Precision*, *Recall* and F_1 *score* as evaluation indicators. In the following equation, the data samples are classified as true positive (true positive, TP), true negative (true negative, TN), false positive (false positive, FP) and false negative (false negative, FN) according to the combination of their true results and the prediction results of the model. Accuracy refers to the ratio of the number of samples predicted by the model to the total number of samples, as shown in Equation (34).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{34}$$

Precision refers to the ratio of the number of samples that the model predicts to be true and the number of samples that are actually true to the number of samples predicted by the model to be true, as shown in Equation (35).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{35}$$

Recall is the ratio of the number of samples in which both the predicted and actual results of the model are true to the actual number of true samples, as shown in Equation (36).

$$\text{Recall} = \frac{TP}{TP + FN} \tag{36}$$

Generally speaking, *Precision* and *Recall* are mutually exclusive. A high precision rate becomes a lower recall rate, and a high recall rate becomes a lower precision rate. Therefore, this paper uses a metric named F-measure that considers both *Precision* and *Recall*. *Precision* and *Recall* are the two components of F-measure [42]. The F-measure value increases proportionally with the increase in *Precision* and *Recall*, as shown in Equation (37).

$$F\text{-}measure = \frac{\left(1+\beta^2\right) \times Precision \times Recall}{Precision + Recall} \tag{37}$$

β is a coefficient of relative importance that is used to adjust *Precision* to *Recall*. This study sets the β to 1, which represents equal consideration of importance in *Precision* and

Recall. This performance measure can also be referred to as the F_1 *score* [43]. The F_1 *score* value is the summed average of the *Precision* and *Recall*.

$$F_1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{38}$$

4. Experimental Results

4.1. Dataset Production

To verify the effectiveness of the method in this paper, the roads in the Yangjiaping area of the Jiulongpo District, Chongqing, were selected as the observation objects for simulation experiments. The monitoring data of several roads in the traffic road network are collected to form the monitoring dataset for traffic situation awareness and the monitoring dataset for the traffic trend prediction, respectively.

4.1.1. Traffic Situational Awareness Monitoring Dataset

The monitoring dataset of traffic situational awareness is based on the traffic flow data of the Yangjiaping road in the Jiulongpo area of Chongqing for a total of one day from 0:00 on 21 November 2021, to 24:00 on 21 November 2021. It is a total of 100 samples, and the size of the time interval of the data indicator is 15 min. In this paper, road traffic status identification is performed based on the traffic flow data. The monitoring data are shown in Table 4.

Table 4. Selected data from the traffic situational awareness dataset.

Number	Time	Traffic Flow (pcu/15 min)
1	00:00	90
2	00:15	60
3	00:30	114
4	00:45	120
5	01:00	180
...	...	...

4.1.2. Traffic Trend Prediction Monitoring Dataset

The monitoring dataset of the traffic trend prediction section is based on the monitoring data of multiple roads in Yangjiaping, Jiulongpo District, Chongqing, at the time of 2:00 p.m. on 21 November 2021, with a total of 250 sets of data samples. Each set of pieces contains monitoring information of ten traffic situation assessment index parameter values for four roads. In this paper, road traffic trends are predicted according to the traffic situation assessment indexes. The monitoring data of traffic trend prediction are shown in Table 5.

Table 5. Selected data from the traffic trend prediction dataset.

Number	Road Length (km)	Road Width (m)	Traffic Lights	Intersections	Road Enforcement Officers	Traffic Flow (pcu/15 min)	Road Construction and Maintenance	Rainfall (mm /min)	Temperature (°C)	Visibility (m)
1	0.981	15	2	7	6	52	0	1.1	8	400
2	1.141	14	5	2	4	48	1	0.5	8	600
3	0.766	15	2	2	2	72	0	0.5	11	600
4	1.236	10	3	11	2	98	1	0.3	9	750
5	1.374	7	2	3	0	26	3	0.8	8	400
6	2.279	9	3	14	3	46	2	0.6	8	600
...	...	...	...	...	...	...	...	...	...	...

4.2. Correlation Analysis of Indicators

4.2.1. Parameter Estimation of the Poisson Regression Model

In this paper, the simulation analysis of the Poisson regression model is carried out for urban road traffic situation prediction indicators, and the results of the Poisson regression model parameter estimation are shown in Table 6.

It can be seen through the results that:

(1) The parameter estimation results of the Poisson regression model show that six indicators—road length, intersection, rainfall intensity, visibility, traffic flow and road construction—have significant effects on urban road emergencies. Among them, there are two indicators of road factors: road length (satisfying the confidence level of 0.01 significance level) and intersection (satisfying the confidence level of 0.01 significance level); there are two indicators of environmental factors: rainfall intensity (satisfying the confidence level of 0.05 significance level) and visibility (satisfying the confidence level of 0.05 significance level); there are two indicators of human factors: traffic flow (satisfying the confidence level of 0.05 significance level) and road construction (satisfying a confidence level of 0.01 significance level).

(2) The regression coefficients of each influencing factor in the Poisson regression model are consistent with the positive and negative signs, so it can be inferred that when keeping the value of the remaining influencing factors constant, only considering the road length, one-way road width, intersections and rainfall, and one of the four influencing factors change, the likelihood of urban road emergencies will show the trend of increasing with the value of the influencing factors; when keeping the value of the remaining influencing factors constant, only considering traffic lights, temperature, visibility, law enforcement officers, traffic flow and road sections under construction, and one of the six influencing factors change, the likelihood of urban road emergencies will show the trend of increasing with the value of the influencing factors; when keeping the value of the remaining influencing factors constant, only considering traffic lights, temperature, visibility, law enforcement officers, traffic flow, and road sections under construction, and one of the six influencing factors change, the possibility of urban road emergencies will show a trend of decreasing with the increase in the value of influencing factors.

Thus, it can be determined that the four positive indicators are road length, one-way road width, the intersections and rainfall; the six negative indicators are traffic lights, temperature, visibility, law enforcement officers, traffic flow and road sections under construction.

Table 6. Results of parameter estimation of the Poisson regression model.

Indicator	Standard Error	Coefficient	*Z*	*p*
Constant	0.297	3.195	10.741	0.000 ***
Road length (km)	0.034	0.136	4.048	0.009 ***
Road width (m)	0.012	0.008	0.658	0.511
Traffic lights	0.016	−0.026	−1.608	0.108
Intersections	0.017	0.045	2.663	0.008 ***
Road enforcement officers	0.014	−0.005	−0.353	0.724
Traffic flow (pcu/15 min)	0.001	−0.001	−2.739	0.023 **
Road construction and maintenance	0.024	−0.023	−4.961	0.006 ***
Rainfall (mm/min)	0.17	0.429	2.53	0.011 **
Temperature (°C)	0.009	−0.012	−1.345	0.179
Visibility (m)	0.0	−0.001	−2.443	0.015 **

Note: *, **, *** represent significance with significance levels of 0.1, 0.05 and 0.01, respectively.

4.2.2. Analysis of Test Results of Poisson Regression Model

The Poisson regression model is tested using the correlation method in Section 2.2.3, and the results of the model are shown in Table 7.

The test result of the Poisson regression model in Table 7 is $p(\chi^2) < 0.001$, which indicates that the Poisson regression model passed the significance test; secondly, since the value of the log-likelihood function of the Poisson regression model is greater than the value of the likelihood function that retains only the constant term, it indicates a better fit of the model. The analysis of the correlation between urban road emergencies and these indicators using the Poisson regression model is reliable. The results of this regression model analysis can be used in this research for urban road traffic situation assessment under emergencies.

Table 7. Results of the Poisson regression model test.

Inspection Index	Poisson Regression Model
χ^2	$\chi^2 = 566.58, p(\chi^2) < 0.001$
LL_C	-1091.695
LL	-808.405
AIC	1654.811
BIC	1725.928

4.2.3. Analysis of Urban Road Emergencies and Road Correlation

Some previous research suggested that traffic managers should establish traffic management strategies for urban roads to reduce the consequences of emergencies. Moreover, they should reconsider certain aspects of urban roadway and street design to harmonize transportation systems, land use and redevelopment. Their research focuses more on pedestrians and streets. The research in [44] achieves accident reduction by incorporating pedestrian safety considerations into the planning, design, implementation and management of urban transportation. There is also a systematic and team-based approach to redesigning transit streets to improve pedestrian, bicycle and public transport traffic and safety [45].

Based on the results of the correlation analysis between emergency events and urban road traffic situation prediction indicators, we could conclude that there is a certain correlation between both of them. It is reliable to analyze urban road emergencies from three aspects: road, environment and human factors, so these indicators could be used as urban road traffic condition assessment indicators under emergencies.

These indicators have been divided into positive and negative indicators of urban road emergencies in Section 4.2.1.

According to Equation (16), when the positive indicators of urban road emergencies values increase, the possibility of urban road emergencies increases; therefore, for the positive indicators, traffic managers should reduce the increase in these indicator values in order to reduce the occurrence of emergencies or reduce the impact. For the road length and one-way road width, we can suggest the traffic decision makers to re-plan the road parameters appropriately. For the intersections, traffic managers need to focus on the roads with multiple intersections. For rainfall, traffic managers need to focus on the road areas with heavy rainfall and provide traffic alerts for those roads.

Similarly, according to Equation (17), it can be seen that when the negative indicators of urban road emergencies increase in value, the possibility of urban road emergencies show a decreasing trend. For the negative indicators, traffic managers will choose to increase these indicators in order to maintain the normal urban road traffic operation. For traffic lights, law enforcement officers and road sections under construction, we could suggest the traffic managers strengthen the road traffic facilities, law enforcement and construction to ensure the smooth operation of road traffic; for visibility, traffic managers should implement traffic strategies to increase the brightness of street lights on roads with poor visibility; for temperature, traffic managers should pay attention to road conditions (icy roads, snowy roads, etc.) in low-temperature road sections and provide travel reminders; for the traffic flow, traffic managers should adopt reasonable traffic diversion strategies to ensure roads are normal.

4.3. Data Pre-Processing

In Section 4.2 of the analysis of the correlation between emergencies and urban roads, this paper has divided the indicators into positive and negative indicators based on the results. It is divided into four positive indicators and six negative indicators. The four positive indicators are road length (km) U_{11}, one-way road width (m) U_{12}, intersections U_{14} and rainfall (mm/min) U_{21}; the six negative indicators are traffic lights U_{13}, temperature (°C) U_{22}, visibility (m) U_{23}, law enforcement officers U_{31}, traffic flow (vehicles/min) U_{32} and road sections under construction U_{33}. Standardized processing is carried out to obtain the measured data of each road, and one set of data after processing is shown in Table 8, where the $(+)$ sign before the indicator indicates a positive indicator, and the $(-)$ sign before the indicator indicates a negative indicator.

Table 8. A set of measured data on urban roads under an emergency.

Road Number	$+U_{11}$	$+U_{12}$	$-U_{13}$	$+U_{14}$	$+U_{21}$	$-U_{22}$	$-U_{23}$	$-U_{31}$	$-U_{32}$	$-U_{33}$
A_1	0.981	15	2	7	1.1	8	400	6	52	0
A_2	1.141	14	5	2	0.5	8	600	4	48	1
A_3	0.766	15	2	2	0.5	11	600	2	72	0
A_4	1.236	10	3	11	0.3	9	750	2	98	1
A_5	1.374	7	2	3	0.8	8	400	0	26	3
A_6	2.279	9	3	14	0.6	8	600	3	46	2

The original dataset D was introduced as:

$$D = \begin{bmatrix} 0.981 & 15 & 2 & 7 & 6 & 52 & 0 & 1.1 & 8 & 400 \\ 1.141 & 14 & 5 & 2 & 4 & 48 & 1 & 0.5 & 8 & 600 \\ 0.766 & 15 & 2 & 2 & 2 & 72 & 0 & 0.5 & 11 & 600 \\ 1.236 & 10 & 3 & 11 & 2 & 98 & 1 & 0.3 & 9 & 750 \\ 1.374 & 7 & 2 & 3 & 0 & 26 & 3 & 0.8 & 8 & 400 \\ 2.279 & 9 & 3 & 14 & 3 & 46 & 2 & 0.6 & 8 & 600 \end{bmatrix}_{6\times10}.$$

Data processing is performed in this set of original data matrix D to obtain a normalized data matrix D^*, as shown in Equation (39).

$$D^* = \begin{bmatrix} 0.1421 & 1 & 1 & 0.4167 & 0 & 0.6389 & 1 & 0 & 1 & 0 \\ 0.2479 & 0.875 & 0 & 0 & 0.33 & 0.6944 & 0.67 & 0.75 & 1 & 0.5714 \\ 0 & 1 & 1 & 0 & 0.67 & 0.3611 & 1 & 0.75 & 0 & 0.5714 \\ 0.3106 & 0.375 & 0.667 & 0.75 & 0.67 & 0 & 0.67 & 1 & 0.67 & 1 \\ 0.4019 & 0 & 1 & 0.0833 & 1 & 1 & 0 & 0.375 & 1 & 0 \\ 1 & 0.25 & 0.667 & 1 & 0.5 & 0.7222 & 0.33 & 0.625 & 1 & 0.5714 \end{bmatrix}_{6\times10} \quad (39)$$

4.4. Analysis of Results

4.4.1. Experiment 1: Traffic Situational Awareness

The road traffic status identification is performed based on the monitoring dataset of traffic situation awareness as an example. Figure 5 shows the results of the road traffic situation awareness of the Yangjiaping road section on 21 November 2021. The horizontal coordinate is the time, and the time range is from 0:00 a.m. to 24:00 a.m. The interval of each dataset is 15 min. In contrast, the vertical coordinate is the calculated traffic situation level.

From the graph, we can see that after daytime, the number of travelers starts to increase, and the traffic pattern is in a state of constant change. During the period from 0:00 to 5:00 (horizontal coordinates 0–20 in the figure), there are inevitable fluctuations in traffic flow on the roadway, and the traffic pattern is generally smooth. During the morning peak hours of 8:00 to 10:00 (horizontal coordinates 32–40 in the figure), there is a clear trend of fluctuation, indicating that the number of vehicles is increasing at this time. At the same time, also during this period, the traffic situation level reached the highest value of the day, indicating that the situation level obtained through the calculation is generally consistent.

In addition, there are fluctuations in the values of the situation level between 21:00 and 23:00 (horizontal coordinates 84–92 in the figure), which is due to the fact that only a single factor of traffic flow is considered, without considering the influence of other factors, which has some errors on the evaluation results. Still, the situation prediction results are in transition from moderate congestion to the open state.

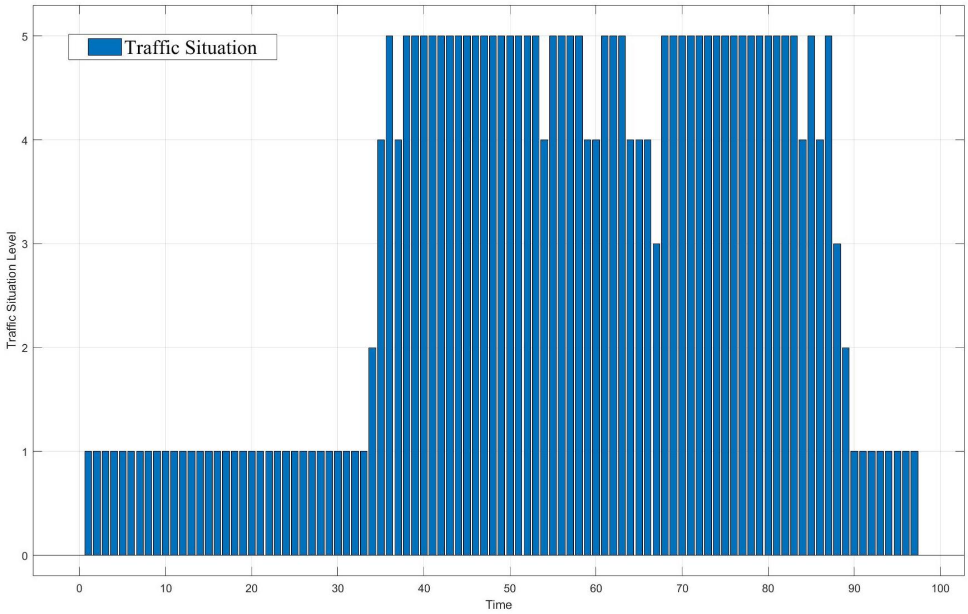

Figure 5. Road traffic situational awareness results.

For an intuitive comparison, the traffic flow data and the traffic situational awareness results of the road section are selected for comparison. The comparison of the road traffic flow and situation awareness results is shown in Figure 6.

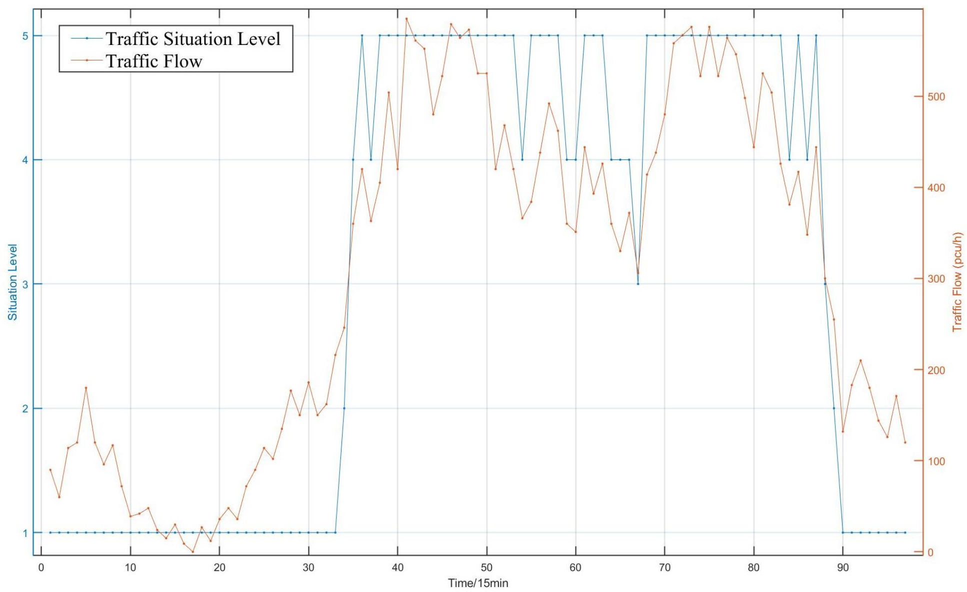

Figure 6. Comparison of the road traffic flow and situation awareness results.

According to the data in the figure, the traffic flow of this road section fluctuates in the interval of [0,200] from 0:00 to 5:00 a.m., and the traffic situation identification result is smooth on the whole. From 5:00 to 9:00 a.m., the traffic flow generally increases and has a significant fluctuation trend, and the road traffic situation level in this period gradually changes from an open state to a severely congested state, which is consistent with the traffic state entering the morning peak period. From 9:00 to 10:00, the traffic situation perception results change dynamically among three levels of light, moderate and severe congestion. From 10:00 to 12:00, the traffic flow decreases, and the traffic pattern level changes from moderate congestion to smooth traffic flow.

The purpose of travel in the vicinity of the study area is mostly commuting to work and school, and often the workplace (destination) and home (origin) are not in the same area, which can cause a surge in road traffic flow. The calculated road traffic situation values fluctuate significantly from 8:00 to 10:00 (horizontal coordinates 32–40 in the figure). This corresponds to the state of the road in the morning peak. The evening peak of the road starts at 17:00 (horizontal coordinate 68 in the figure), when residents start to leave school or go home from work. Residents return to their home (destination) from their workplace and school (origin), which also causes traffic fluctuations. In contrast to the morning peak, the evening peak lasts for a long time. The reason for this is that the residents have their time allocated more freely in the evening, which could lead them to spend more time on the city roads. Thus, the road traffic flows continue to be large, with the evening peak ending at 22:00 (horizontal coordinate 88 in the figure).

From Figure 6, we can also find that there is still a mismatch between some road traffic situation levels and traffic flow: when the traffic flow value reaches the maximum value of the current time period, the calculated road traffic situation does not reach the maximum value, but the result is low; when the traffic flow decreases, the road traffic situation is still on the high side. Actually, this is because this paper only uses a single indicator to calculate the road traffic trend, in which the parameters between road traffic trend and traffic flow may have some deviation, so these cases occur. Generally speaking, the road traffic situation values calculated in this paper and the trend of actual traffic flow are basically consistent.

4.4.2. Experiment 2: Calculation of Indicators' Weights for Traffic Trend Prediction

The road traffic situation indicators were analyzed by the AHP method, and the weights of the four first-level indicators in the criterion layer were $W_U = [0.072, 0.279, 0.649]$. According to the criteria of the average randomness indicator in Table 3, the CR of the criterion layer is $CR = 0.009 < 0.1$, which satisfies the consistency test. Then, the weights of the indicator layer are calculated. The indicator layer weights—W_{U_1} for the Road Factors U_1, W_{U_2} for the Natural Factors U_2, and W_{U_3} for the Human Factors U_3—are $W_{U_1} = [0.053, 0.106, 0.255, 0.586]$, $W_{U_2} = [0.263, 0.079, 0.659]$, and $W_{U_3} = [0.777, 0.153, 0.070]$. The CI and CR of the three indicator layers are less than 0.1 at $CR_1 = 0.027$, $CR_2 = 0.009$ and $CR_3 = 0.009$, which satisfies the consistency test. The results of the weights are shown in Table 9.

Table 9. The weighting of road traffic trend indicators for the AHP method.

Guideline Layer U	Guideline Layer Weights	Indicator Layer	AHP Weights
Road Factors U_1	0.072	U_{11}	0.00381
		U_{12}	0.00763
		U_{13}	0.01836
		U_{14}	0.04219
Natural Factors U_2	0.279	U_{21}	0.07337
		U_{22}	0.02204
		U_{23}	0.18386
Human Factors U_3	0.649	U_{31}	0.504
		U_{32}	0.0993
		U_{33}	0.0454

The final AHP method calculates the weights of road traffic trend indicators under emergencies, as shown in Equation (40).

$$W_1 = [0.00381, 0.00763, 0.01836, 0.04219, 0.07337, 0.02204, 0.18386, 0.504, 0.09930, 0.0454] \quad (40)$$

Similarly, the results of the objective weights of the indicators determined by the EM method are shown in Table 10.

Table 10. The weighting of road traffic trend indicators for the EM method.

Guideline Layer U	Guideline Layer Weights	Indicator Layer	EM Weights
Road Factors U_1	0.524	U_{11} U_{12} U_{13} U_{14}	0.053 0.080 0.223 0.168
Natural Factors U_2	0.183	U_{21} U_{22} U_{23}	0.060 0.051 0.072
Human Factors U_3	0.293	U_{31} U_{32} U_{33}	0.073 0.083 0.137

The objective weights of the three first-level indicators in the criterion layer are $[0.524, 0.183, 0.293]$. The objective weights of the four second-level indicators under the guideline layer of Road Factors U_1 are $[0.053, 0.080, 0.223, 0.168]$, the objective weights of the three second-level indicators under the guideline layer of Natural Factors U_2 are $[0.060, 0.051, 0.072]$, and the objective weights of the three second-level indicators under the guideline layer of Human Factors U_3 are $[0.073, 0.083, 0.137]$. The weights calculated by the final EM method are shown in Equation (41).

$$W_2 = [0.053, 0.08, 0.223, 0.168, 0.06, 0.051, 0.072, 0.073, 0.083, 0.137] \tag{41}$$

The weights of the traffic trend indicators were calculated using the GT-AHP-EM method, and the weighting results are shown in Table 11. The combination coefficients of the AHP and EM weighting methods were $\alpha_1{}^* = 0.6666312219719346$ and $\alpha_2{}^* = 0.3333687780280654$, respectively. The objective weights of the four first-level indicators in the criterion layer were $[0.2225, 0.2472, 0.5303]$. The final GT-AHP-EM weights are shown in Equation (42).

$$W^* = [0.0202, 0.0317, 0.0865, 0.0841, 0.0689, 0.0317, 0.1466, 0.3605, 0.0939, 0.0759] \tag{42}$$

Table 11. The weighting of road traffic trend indicators for the GT-AHP-EM method.

Guideline Layer U	Guideline Layer Weights	Indicator Layer	GT-AHP-EM Weights
Road Factors U_1	0.2225	U_{11} U_{12} U_{13} U_{14}	0.0202 0.0317 0.0865 0.0841
Natural Factors U_2	0.2472	U_{21} U_{22} U_{23}	0.0689 0.0317 0.1466
Human Factors U_3	0.5303	U_{31} U_{32} U_{33}	0.3605 0.0939 0.0759

In the road traffic situation assessment model under emergencies, from the weights calculated by the GT-AHP-EM method, the weight of the road section law enforcement officers (U_{31}) is the largest. Once an urban road emergency occurs, the road section law enforcement officers can quickly maintain the traffic order of that road and reduce the impact caused by the emergency. The number of law enforcement officers determines the length of time for the road to restore stability, so the traffic management process after urban road emergencies should be carried out in the intersections prone to emergencies with reasonable arrangements of law enforcement officers to do an excellent job of emergency disposal to reduce losses. Visibility (U_{23}) is the second factor that affects the road after urban road emergencies. The higher the visibility after an emergency event, the more rapid the traffic management emergency disposal will be. If visibility is low, the probability of secondary traffic events increases and more unknown situations are likely to occur. Urban road monitoring and early warning should be strengthened and protected on roads with low visibility.

The results of AHP, EM and GT-AHP-EM methods are shown in Figure 7, which are highly subjective and depend on the subjective intention and experience of decision makers. The weights of the indicators determined by the decision makers relying on the empirical judgment of the traffic state and the weights of the indicators obtained by using objective data analysis will be different, respectively. The road factor is static, and the decision makers prefer to choose to combine their own summarized experience to judge the traffic status, so the six indicators of road length U_{11}, one-way road width U_{12}, number of traffic lights U_{13}, number of intersections U_{14}, number of roadway law enforcement officers U_{31} and number of road sections under construction U_{33} in Figure 7 are calculated by the AHP method and EM method. The results vary greatly. The indicators of natural factors have been studied a lot, and there are specific operation rules summarized, so the results of the weights calculated by the AHP method and the EM method are similar in the four indicators of rainfall intensity U_{21}, temperature U_{22}, visibility U_{23} and traffic flow U_{32}.

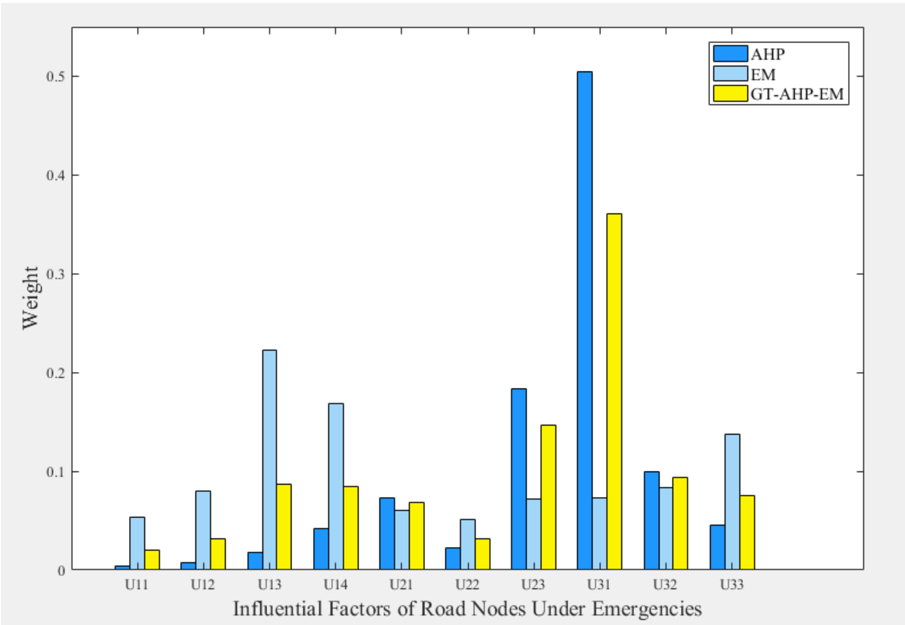

Figure 7. Comparison of the weights of traffic trend indicators calculated by 3 methods.

4.4.3. Experiment 3: Traffic Trend Prediction

This traffic trend prediction experiment prepares traffic data of illegal red light running events on Yangjiaping road in Jiulongpo District, Chongqing, for six months in 2020. In this paper, the road trends are calculated using the mentioned road traffic trend prediction method. The results are the predicted roads that vehicles are monitored after the event, and the data of the control group are the actual road choices of vehicles.

We compared the results of the proposed GT-AHP-EM method with AHP, EM and some well-known methods for road traffic situation assessment, such as the Combination of the Entropy Method and Variation Coefficient Method (EM-VC) [46] and the Bayesian network (BN) [47]. We performed the prediction evaluation based on the four metrics presented in Section 3.3. The results of the comparison with the four methods are shown in Table 12.

As shown in Table 12, the proposed GT-AHP-EM method has the best overall *Accuracy* and *Precision* on the Traffic Trend Prediction Monitoring Dataset. Compared with the EM-CV method, the GT-AHP-EM method has slightly higher *Accuracy* and *Precision* (both 0.23% more). However, the *Recall* (0.41% lower) and *F*1 *score* (0.07% lower) are slightly lower.

The actual monitoring results of the dataset in this experiment are only 0 and 1. The 0 in the result means that the vehicle data associated with the emergency were not monitored after the event, and the 1 means that the vehicle information associated with the emergency was monitored. Once there is similar vehicle information with the emergency event, such as the same vehicle model, wrong license plate number identification, etc., it may be misjudged that the emergency event has affected the road traffic, and the final monitoring results will conclude that the emergency event has some impact on the road. This will lead to the occurrence of certain errors in the actual monitoring results and affect the evaluation of various methods in the predication comparison.

Table 12. Comparison of five methods of evaluation.

Method	*Accuracy*	*Precision*	*Recall*	F_1 *Score*
AHP	0.7336	0.7336	0.6487	0.6874
EM	0.7539	0.7539	0.7491	0.7510
EM-VC	0.7808	0.7808	0.8213	0.8005
BN	0.7654	0.7654	0.8065	0.7872
GT-AHP-EM	0.7831	0.7831	0.8172	0.7998

5. Conclusions and Future Work

5.1. Conclusions

The complexity of urban road traffic means that decision makers need to assess the road traffic situation under emergencies, and the assessment results will help them in traffic management. The accuracy of the assessment results is essential to determine the management of road traffic decisions under emergencies.

The paper constructs an urban road monitoring network by road geographic location relationship and studies the assessment of the urban road situation under emergencies by reviewing the correlation between emergencies and traffic data. Through these logical relationships, a collaborative monitoring model of urban road traffic dynamics under emergencies is established to comprehensively assess road traffic conditions.

The following conclusions can be drawn:

1. Previous studies have more often used individual roads where emergencies occur to build road traffic situation assessment models, and they focus on the completeness and real-time nature of the entire model process. This study proposes a collaborative monitoring method based on the traffic road network. Compared with previous studies, the data input of this method is more diversified, which is reflected in both the types of monitoring indicators and monitoring targets. The previous studies were evaluated by single indicators, so the results were more dependent on the attributes and accuracy of the monitoring indicators. In contrast, the results are more informative by using multiple indicator data fusion calculation. The monitoring target diversification refers to the data input sources from different urban road nodes. The data obtained in this way will be more reliable and comprehensive. This method starts with a single road node monitoring an emergency, goes through collaborative nodes to provide data support and finally calculates the impact of the event on the whole traffic road network. It monitors urban road traffic in a multi-node monitoring way.
2. The GT-AHP-EM method is proposed in the process of indicator assignment for situational prediction. It not only reduces the artificial factor of subjective assignment method, but also fully considers the influence of objective data. The method reconciles the contradiction between subjective weights and objective weights and improves the scientific rationality of the assignment to a certain extent. The experimental results show that the method uses traffic flow as the model input for traffic state identification in the process of traffic situational awareness, and the output results are

consistent with the objective laws of road traffic. When the method is used for traffic trend prediction, the accuracy of the prediction results is improved by 2.7% and 0.7% compared with the AHP and EM methods, respectively. Therefore, the validity and rationality of the model were proven.

3. This study can be continued to dig deeper in terms of data sources, scenario conditions, etc. The experimental data sources are all collected through road sensor devices, and the monitoring data are easily collected and the data quantity is huge. We could consider this feature to carry out other studies in the traffic field for different research targets and scenarios and analyze the road, vehicles and pedestrians under different time periods for multiple roads. Meanwhile, the emergency event selected for the experimental part of this study is an illegal red light running event, which is used as a case to conduct analysis and verification. The experimental results show that this study has some feasibility. However, we need to select other data to verify the applicability of this model to different emergencies.

5.2. Future Work

The limitations of our study include that we have conducted the primary evaluation of the traffic situation of the roads in the system in a specific scenario. In the near future, we will enhance the system by introducing mobile edge computing to reduce latency and enhance the reliability and validity of the monitoring data. Indeed, the system requires a comprehensive filtering and fusion calculation of the data from the situational assessment metrics system, which we intend to address in future work.

Moreover, when assessing the urban road traffic situation under emergencies in this research, we follow such rules for the selection of indicators. Firstly, we made a preliminary screening from previous research and then analyzed the relevance of the indicators to the emergencies for determination. However, this approach is rather general, and we have not carried out a specific dissection of various indicators' compositions. A case in point is the traffic flow indicator. In fact, different vehicles are affected by emergencies differently within urban roads, and they all affect the changes in urban road traffic situations. We may analyze the specific vehicle composition of traffic flow with details in our future work, thus providing assistance to traffic managers in establishing traffic management strategies to maintain road traffic operation for emergencies.

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References

1. Goodchild, M.F. Geographic information systems and disaggregate transportation modeling. *Geogr. Syst.* **1998**, *5*, 19–44.
2. Nzouonta, J.; Rajgure, N.; Wang, G.; Borcea, C. VANET routing on city roads using real-time vehicular traffic information. *IEEE Trans. Veh. Technol.* **2009**, *58*, 3609–3626. [CrossRef]
3. He, Y.; Liu, Z.; Shi, J.; Wang, Y.; Zhang, J.; Liu, J. K-shortest-path-based evacuation routing with police resource allocation in city transportation networks. *PLoS ONE* **2015**, *10*, e0131962. [CrossRef]

4. Guo, Q.; Wang, H.; He, J.; Zhou, C.; Liu, Y.; Xing, B.; Jia, Z.; Li, M. Graphic simplification and intelligent adjustment methods of road networks for navigation with reduced precision. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 490. [CrossRef]
5. Wang, G.; Xu, Z.; Wen, F.; Wong, K.P. Traffic-constrained multiobjective planning of electric-vehicle charging stations. *IEEE Trans. Power Deliv.* **2013**, *28*, 2363–2372. [CrossRef]
6. Clouqueur, T.; Phipatanasuphorn, V.; Ramanathan, P.; Saluja, K.K. Sensor deployment strategy for target detection. In Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications, Atlanta, GA, USA, 28 September 2002; pp. 42–48.
7. Palade, C.; Stavarache, I.; Stoica, T.; Ciurea, M.L. GeSi nanocrystals photo-sensors for optical detection of slippery road conditions combining two classification algorithms. *Sensors* **2020**, *20*, 6395. [CrossRef]
8. Chen, L.; Ma, Y.; Zhang, Y.; Liu, J. Obstacle avoidance and multitarget tracking of a super redundant modular ma-nipulator based on Bezier curve and particle swarm optimization. *Chin. J. Mech. Eng.* **2020**, *33*, 71. [CrossRef]
9. Ghasemi, P.; Khalili-Damghani, K.; Hafezalkotob, A.; Raissi, S. Uncertain multi-objective multi-commodity multi-period multi-vehicle loca-tion-allocation model for earthquake evacuation planning. *Appl. Math. Comput.* **2019**, *350*, 105–132.
10. Jiang, P.; Li, R.; Li, H. Multi-objective algorithm for the design of prediction intervals for wind power forecasting model. *Appl. Math. Model.* **2019**, *67*, 101–122. [CrossRef]
11. Cai, B.; Xie, M.; Liu, Y.; Liu, Y.; Feng, Q. Availability-based engineering resilience metric and its corresponding evaluation methodology. *Reliab. Eng. Syst. Saf.* **2018**, *172*, 216–224. [CrossRef]
12. Guo, Y.; Sayed, T.; Essa, M. Real-time conflict-based Bayesian Tobit models for safety evaluation of signalized intersections. *Accid. Anal. Prev.* **2020**, *144*, 105660. [CrossRef] [PubMed]
13. Xing, Y.; Lv, C.; Wang, H.; Wang, H.; Ai, Y.; Cao, D.; Velenis, E.; Wang, F.Y. Driver lane change intention inference for intelligent vehicles: Framework, survey, and challenges. *IEEE Trans. Veh. Technol.* **2019**, *68*, 4377–4390. [CrossRef]
14. Wang, Z.; Wu, Y.; Niu, Q. Multi-sensor fusion in automated driving: A survey. *IEEE Access* **2019**, *8*, 2847–2868. [CrossRef]
15. Abdulsalam, Y.; Hossain, M.S. COVID-19 networking demand: An auction-based mechanism for automated selection of edge computing services. *IEEE Trans. Netw. Sci. Eng.* **2020**, *9*, 308–318.
16. Zamanifar, M.; Hartmann, T. Decision attributes for disaster recovery planning of transportation networks; A case study. *Transp. Res. Part D Transp. Environ.* **2021**, *93*, 102771. [CrossRef]
17. Balmat, J.F.; Lafont, F.; Maifret, R.; Pessel, N. A decision-making system to maritime risk assessment. *Ocean Eng.* **2011**, *38*, 171–176. [CrossRef]
18. Alsarhan, A.; Kilani, Y.; Al-Dubai, A.; Zomaya, A.Y.; Hussain, A. Novel fuzzy and game theory based clustering and decision making for VANETs. *IEEE Trans. Veh. Technol.* **2019**, *69*, 1568–1581. [CrossRef]
19. Amiri, I.S.; Prakash, J.; Balasaraswathi, M.; Sivasankaran, V.; Sundararajan, T.; Hindia, M.; Tilwari, V.; Dimyati, K.; Henry, O. DABPR: A large-scale internet of things-based data aggregation back pressure routing for disaster management. *Wirel. Netw.* **2020**, *26*, 2353–2374. [CrossRef]
20. Sun, X.; Lin, K.; Jiao, P.; Lu, H. The dynamical decision model of intersection congestion based on risk identi-fication. *Sustainability* **2020**, *12*, 5923. [CrossRef]
21. Zhang, Y.; Lu, Y.; Yang, G.; Hang, Z. Multi-Attribute Decision Making Method for Node Importance Metric in Complex Network. *Appl. Sci.* **2022**, *12*, 1944. [CrossRef]
22. Tian, Z.; Zhang, S. Application of multi-attribute group decision-making methods in urban road traffic safety evaluation with interval-valued intuitionistic fuzzy information. *J. Intell. Fuzzy Syst.* **2021**, *40*, 5337–5346. [CrossRef]
23. Gupta, P.; Mehlawat, M.K.; Aggarwal, U.; Charles, V. An integrated AHP-DEA multi-objective optimization model for sustainable transportation in mining industry. *Resour. Policy* **2018**, *74*, 101180. [CrossRef]
24. Han, Y.; Wang, Z.; Lu, X.; Hu, B. Application of AHP to road selection. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 86. [CrossRef]
25. Tumsekcali, E.; Ayyildiz, E.; Taskin, A. Interval valued intuitionistic fuzzy AHP-WASPAS based public transportation service quality evaluation by a new extension of SERVQUAL Model: P-SERVQUAL 4.0. *Expert Syst. Appl.* **2021**, *186*, 115757. [CrossRef]
26. Huang, W.; Zhang, Y.; Yu, Y.; Xu, Y.; Xu, M.; Zhang, R.; De Dieu, G.J.; Yin, D.; Liu, Z. Historical data-driven risk assessment of railway dangerous goods transportation system: Comparisons between Entropy Weight Method and Scatter Degree Method. *Reliab. Eng. Syst. Saf.* **2021**, *205*, 107236. [CrossRef]
27. Zhang, M.; Zhang, D.; Fu, S.; Kujala, P.; Hirdaris, S. A predictive analytics method for maritime traffic flow complexity estimation in inland waterways. *Reliab. Eng. Syst. Saf.* **2022**, *220*, 108317. [CrossRef]
28. Tang, L.; Lu, Z.; Fan, B. Energy efficient and reliable routing algorithm for wireless sensors networks. *Appl. Sci.* **2020**, *10*, 1885. [CrossRef]
29. Dong, X.; Qian, M.; Jiang, R. Packet classification based on the decision tree with information entropy. *J. Supercomput.* **2020**, *76*, 4117–4131. [CrossRef]
30. Blagojević, A.; Stević, Ž.; Marinković, D.; Kasalica, S.; Rajilić, S. A novel entropy-fuzzy PIPRECIA-DEA model for safety evaluation of railway traffic. *Symmetry* **2020**, *12*, 1479. [CrossRef]
31. von Altrock, C.; Krause, B. Fuzzy logic and neurofuzzy technologies in embedded automotive applications. In Proceedings of the Third International Conference on Industrial Fuzzy Control and Intelligent Systems, Houston, TX, USA, 1–3 December 1993; pp. 55–59.

32. Krause, B.; von Altrock, C.; Pozybill, M. Intelligent highway by fuzzy logic: Congestion detection and traffic control on multi-lane roads with variable road signs. In Proceedings of the IEEE 5th International Fuzzy Systems, New Orleans, LA, USA, 11 September 1996; Volume 3, pp. 1832–1837.
33. *Highway Capacity Manual 2010 (HCM2010)*; Transportation Research Board, National Research Council: Washington, DC, USA, 2010; Volume 1207.
34. Guiyan, J. *Road Traffic State Discrimination Technology and Application*, 1st ed.; China Communications Press: Beijing, China, 2004.
35. Zou, H.; Cao, K.; Jiang, C. Spatio-Temporal Visual Analysis for Urban Traffic Characters Based on Video Surveillance Camera Data. *ISPRS Int. J. Geo Inf.* **2021**, *10*, 177. [CrossRef]
36. Zhu, Q. Research on road traffic situation awareness system based on image big data. *IEEE Intell. Syst.* **2019**, *35*, 18–26. [CrossRef]
37. Hofbauer, J.; Sigmund, K. Evolutionary game dynamics. *Bull. Am. Math. Soc.* **2003**, *40*, 479–519. [CrossRef]
38. Facchinei, F.; Kanzow, C. Generalized Nash equilibrium problems. *Ann. Oper. Res.* **2010**, *175*, 177–211. [CrossRef]
39. Zanakis, S.H.; Solomon, A.; Wishart, N.; Dublish, S. Multi-attribute decision making: A simulation comparison of select methods. *Eur. J. Oper. Res.* **1998**, *107*, 507–529. [CrossRef]
40. Saaty, T.L. The modern science of multicriteria decision making and its practical applications: The AHP/ANP approach. *Oper. Res.* **2013**, *61*, 1101–1118. [CrossRef]
41. Hu, S.; Jia, Q.; Dong, L.; Han, J.; Guo, M.; Guo, W. An evaluation method for product design solutions for healthy aging compan-ionship. *Front. Public Health* **2022**, *10*, 919300. [CrossRef] [PubMed]
42. Rella Riccardi, M.; Mauriello, F.; Scarano, A.; Montella, A. Analysis of contributory factors of fatal pedestrian crashes by mixed logit model and association rules. *Int. J. Inj. Control. Saf. Promot.* **2022**, 1–15. [CrossRef]
43. Chicco, D.; Jurman, G. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC Genom.* **2020**, *21*, 6. [CrossRef] [PubMed]
44. Montella, A.; Chiaradonna, S.; Mihiel, A.C.d.S.; Lovegrove, G.; Nunziante, P.; Rella Riccardi, M. Sustainable complete streets design criteria and case study in Naples, Italy. *Sustainability* **2022**, *14*, 13142. [CrossRef]
45. Rella Riccardi, M.; Galante, F.; Scarano, A.; Montella, A. Econometric and Machine Learning Methods to Identify Pedestrian Crash Patterns. *Sustainability* **2022**, *14*, 15471. [CrossRef]
46. Zhang, Y.; Zhou, M.; Kong, N.; Li, X.; Zhou, X. Evaluation of Emergency Response Capacity of Urban Pluvial Flooding Public Service Based on Scenario Simulation. *Int. J. Environ. Res. Public Health* **2022**, *19*, 16542. [CrossRef] [PubMed]
47. Xie, M. Research on Urban Road Traffic Situation Assessment Methods under Emergency Events. Master's Thesis, Nanjing University of Science and Technology, Nanjing, China, 2014.