Reliability Evaluation Method of Intelligent Transportation System Based on Deep Learning

Xiaomei Yang(✉)

Guangxi Vocational Normal University, Nanning 530000, China
yxm20221123@163.com

Abstract. Urban road reliability analysis is an important part of traffic condition analysis and research in recent years. The research on road network reliability can provide strong information support for the control, induction, optimization and planning of intelligent transportation systems. In this context, a reliability evaluation method of intelligent transportation system based on deep learning is proposed. Use the Delphi method to select evaluation indicators and build an evaluation index system. The AHP method and factor analysis method were used to calculate the comprehensive weight of the indicators. Based on the deep belief network in deep learning, an evaluation model is constructed, the reliability index is calculated, and the degree of reliability is judged. The test results show that the intelligent transportation system is applied in 9 different administrative regions, and the obtained reliability indexes are all above 1.0, indicating that the reliability of the intelligent transportation system is high.

Keywords: Deep Learning · Intelligent Transportation System · Evaluation Index · Ahp Method · Factor Analysis Method · Reliability Evaluation

1 Introduction

The smart transportation system is a basic, leading and strategic industry for urban development and construction, and an important service industry that meets the needs of urban life and production. The transportation system in the central area of a large city is the lifeblood of the entire city development and the core to ensure the normal operation of the city [1, 2]. A stable, efficient and reliable transportation system is not only the basis for travelers to achieve their travel goals, but also the ultimate goal of urban traffic managers and builders. As socialism with characteristics enters a new era, my country's urbanization process continues to accelerate, and the number of large cities continues to grow. Relevant data show that in 2013, there were seven cities with urban populations exceeding 10 million in my country. In addition to Beijing, Shanghai, Guangzhou and Shenzhen, there were Wuhan, Tianjin and Chongqing; urban populations were between 5 million and 10 million. There are 11 cities, namely Chengdu, Nanjing, Foshan, Dongguan, Xi'an, Shenyang, Hangzhou, Suzhou, Shantou, Harbin, and Hong Kong. As of 2017, the number of large cities with a population of more than 2 million in

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the central area of my country has reached 53, accounting for about 1/4 of the number of large cities in the world. However, with the continuous expansion of the scale of cities, the contradiction between traffic supply and demand in the central areas of large cities has become prominent, the regional road traffic pressure has increased, and the traffic congestion in the central areas of large cities has become more and more serious. Due to congestion, the operational efficiency of the transportation system has decreased, the operating cost has risen, the travel time of traffic participants has been prolonged, and the traffic environment has deteriorated, which has seriously affected the normal conduct of various life and production activities in the region.

How to improve the operation of urban smart transportation system and improve system reliability has become one of the key research contents of my country's transportation industry. The reliability of the intelligent transportation system is not only a comprehensive reflection of the performance of the transportation system, but also one of the theoretical foundations for the construction of ITS. It is the basis and important part of the overall planning, design, traffic flow organization and management of the road network and the formulation of major emergency response plans [3]. In addition, in the case of limited resources, studying the reliability of urban transportation system can rationally allocate existing resources to the greatest extent. Effectively exploring the potential of road network has great theoretical significance and application value for improving the level of urban traffic management and dealing with the harm caused by sudden disasters and emergencies.

Based on the above analysis, a reliability evaluation method of intelligent transportation system based on deep learning is proposed. Select evaluation indicators, build an evaluation indicator system, and calculate the comprehensive weight of indicators. Based on the deep belief network in deep learning, an evaluation model is constructed, the reliability index is calculated, and the degree of reliability is judged. The test results verify that the reliability of the intelligent transportation system is high.

2 Research on Reliability of Intelligent Transportation System

The reliability of smart transportation systems is getting more and more attention. Because significant travel uncertainty not only increases the difficulty and cost of individual travel decisions, but also reduces the efficiency of the transportation system, affects the performance of the system, and even leads to the failure of management measures. Reliability is an important performance index of urban transportation system, and it is a probabilistic description of the transportation function of the system. It is not only affected by static elements such as road network facilities, but also more susceptible to dynamic random demands, which makes the uncertainty of reliability itself more difficult to describe. In many megacities, frequent traffic accidents and road maintenance and other temporary events and natural disasters and other emergencies require the rescue vehicles to arrive at the accident site quickly and in a timely manner under the premise of satisfying accessibility [4]. It can be seen that reliability is different from the general indicators used to describe the operation status of the urban transportation system. It integrates short-term and long-term indicators. It not only represents evaluation criteria, but also has policy connotations. It is a system performance indicator based on a broad basis and belongs to a multidisciplinary research field. Therefore, in-depth discussions are needed from different perspectives such as transportation science, system science, computer science, economics, and behavioral science.

2.1 Construction of Evaluation Index System

Appropriate screening should be carried out for the initially selected evaluation indicators, the primary and secondary indicators should be distinguished, and the main evaluation indicators should be selected to construct an evaluation indicator system. The selection of indicators is usually divided into three steps, that is, to establish the principles of selection of evaluation indicators, to clarify the influencing factors of reliability, and to select and establish indicators.

Selection Principles of Evaluation Indicators
In actual comprehensive evaluation activities, it is not that the more evaluation indicators the better, but the less the better. Therefore, when establishing an evaluation indicator system, the following principles should be followed:

(1) Systematic principle: The index system should be able to fully reflect the essential characteristics and overall performance of the evaluation object, and the overall evaluation function of the index system is greater than the simple sum of the sub-indicators.
(2) Consistency principle: The evaluation index system should be consistent with the evaluation objectives, so as to fully reflect the intention of the evaluation activities.
(3) The principle of independence: the indicators at the same level should not have an inclusive relationship, so as to ensure that the indicators can reflect the actual situation of the system from different aspects.
(4) The principle of measurability: indicators can be measured or measured, and numbers should be used as much as possible.
(5) Scientific principle: Guided by scientific theory and based on the internal elements of the objective system and their essential connections, it correctly reflects the quantitative characteristics of the system as a whole and its internal interrelationships.
(6) The principle of comparability: the stronger the comparability of the index system of the systematic evaluation, the greater the credibility of the evaluation results. In the standardization process of indicators, synchronous trending should be maintained to ensure the comparability between indicators [5].

Clarify the Influencing Factors of Reliability
According to the definition of the research object above, this subsection focuses on analyzing the components of the smart transportation system, laying the foundation for the following article to accurately grasp the urban traffic operation mechanism and find out the reliability indicators that affect the smart transportation system.

The smart transportation system is mainly composed of five parts: traffic flow, road network, traffic management conditions and traffic environment. Among them, traffic participants and transportation modes are collectively referred to as road traffic flow.

The following will analyze the various components of the road transportation system in combination with the actual case of the traffic system in the central area of my country's large cities.

Traffic Participants

Traffic participants include pedestrians, drivers and passengers, and are one of the elements that make up the traffic flow in the central area of a large city. The dynamic and random spatiotemporal distribution characteristics of traffic flow in the central area are mainly due to the uncertainty of the total amount of travel and travel behavior of each traffic participant.

Mode of Transportation

Transportation modes include private cars, conventional buses, rental and online car-hailing, and non-motorized vehicles, which are another major element of traffic flow. The complex and diverse modes of transportation in the central area, its operation mode, the travel proportion of various modes of transportation and the operation status are mainly affected by the travel behavior of traffic participants and the structure and scale of road network infrastructure.

Road Network

A network of various roads within a city is called an urban road network. The road network studied in this paper is the road network in the central area of the city. The road network in the central area of a big city is composed of road sections and intersections in the area. Its formation and development are closely related to the city's politics, economy, culture, functional layout and land use scale.

Traffic Management Conditions

Traffic management conditions include signs and markings, intelligent transportation facilities and corresponding control policies. The purpose of traffic management is to recognize and follow the inherent objective laws of road traffic flow. Use corresponding technical means, methods and measures to continuously improve the efficiency and quality of traffic management. This results in fewer delays, shorter running times, greater capacity, better order and lower operating costs, resulting in the best socio-economic, transportation and environmental benefits.

Traffic Environment

The road traffic environment includes the noise environment and the atmospheric environment. If the noise and air pollution are within the acceptable range, it means that the traffic system in the central area runs smoothly, and the degree of vehicle exhaust emissions and noise pollution is smaller, and vice versa. At present, the road traffic environment in the central areas of my country's large cities is not optimistic. Noise and air pollution are still serious, and the task of environmental governance is still severe.

Selection and Establishment of Indicators

Commonly used index selection methods include Delphi method and principal component analysis method. The Delphi method is used here, also known as the expert prediction method. It distributes multiple rounds of questionnaires to experts in relevant fields to solicit opinions in an anonymous way. These experts do not meet or focus on discussions. Each round of distribution will summarize and revise the opinions of the previous round of experts, and then give feedback, and finally make the results of each expert tend to be consistent, so as to achieve the final research or prediction effect [6].

This paper studies the reliability evaluation index of intelligent transportation system. It is necessary to collect and analyze the opinions of experts who have a certain understanding and qualifications in various aspects of urban transportation, so as to obtain the approval of most experts, so as to construct the evaluation index. During the implementation of the Delphi method, there are always two people in action, one is the organizer of predictions, and the other is the selected experts. The first thing to note is that the questionnaires in the Delphi method are different from the usual ones. In addition to the content of the usual questionnaire to ask questions and ask the respondents to answer, it also has the responsibility of providing information to the respondents, and it is a tool for experts to exchange ideas. The workflow of the Delphi method can be roughly divided into the following steps. In each step, the organizers and experts have different tasks [7].

Step 1: Form an expert group to clarify the research objectives, and determine experts and specialists according to the scope of knowledge required by the project research. The number of experts can be determined according to the size of the research project and the breadth of the scope involved. Generally, about 8–20 people are appropriate.
Step 2: Ask all the experts the questions to be consulted and the relevant requirements, and attach all the background materials on this issue, and ask the experts to ask what materials are needed, and then the experts will make a written reply.
Step 3: According to the materials they received, combined with their own knowledge and experience, each expert put forward their own opinions, and explained the basis and reasons.
Step 4: Summarize and organize the first judgment opinions of the experts, and then distribute them to the experts, so that the experts can compare their different opinions with others, and revise their opinions and judgments. The opinions of the experts can be sorted out or other experts with higher status can be invited to comment, and then these opinions can be distributed to the experts so that they can revise their opinions after reference.
Step 5: Experts adjust and revise their opinions according to the results of the first round of consultation and related materials, and give the basis and reasons for the revised opinions.
Step 6: According to the above steps, collect comments round by round and provide feedback to experts. It usually takes three or four rounds to collect opinions and feedback. When giving feedback to experts, only various opinions are given, but the specific names of the experts who express various opinions are not stated. This process is repeated until each expert stops changing his opinion.

In the above steps, the summary and arrangement of each round of expert opinions is a more important part. According to the above survey, according to the score given by each expert, calculate the positive coefficient, authority coefficient and coordination coefficient.

(1) Positive coefficient

The participating experts will cooperate with the whole investigation in a serious and rigorous manner only if they have a high degree of attention and interest in the research. The expert positivity index can well reflect the degree of concern of the participants to the project to ensure the accuracy of the results. Calculated as follows:

$$A = \frac{a_1}{a_2} \tag{1}$$

In the formula, A represents the positive coefficient, a_1 represents the number of participating experts, a_2 represents the total number of experts.

(2) **Authority coefficient**

In addition to being highly motivated, the experts participating in this research should also ensure that they have an understanding of the fields involved in this research or have long been engaged in industry representatives or leaders in related fields. In mathematical statistics, the authoritative index of experts is used to ensure the reliability of the results. This index can not only measure the basis of experts' judgment on each indicator, but also reflect the expert's familiarity with each indicator. The basis of judgment is generally divided into four aspects, namely theoretical analysis, practical experience, understanding of domestic and foreign peers and intuition. Each aspect is further divided into three degrees of influence, which are large, medium and small, indicating that the degree of influence of the four aspects on the judgment of an indicator is relatively large, medium or small. Each judgment is assigned a numerical value according to the corresponding degree of influence for quantification, as shown in Table 1.

Table 1. Judgment basis and quantitative table of influence degree

Judgment basis	Degree of influence on expert judgment		
	Big	Middle	Small
Theoretical analysis	3	2	1
Practical experience	5	4	3
Understanding of peers at home and abroad	1	1	1
Intuition	1	1	1

To measure the familiarity of experts, there are 6 levels corresponding to 6 points, as shown in Table 2.

The formula for calculating the expert authority coefficient is as follows:

$$B = \frac{b_1 + b_2}{2} \tag{2}$$

In the formula, B is the authority degree of experts, b_1 is the judgment coefficient, and b_2 is the familiarity.

Table 2. The coefficient of familiarity of experts to the problem

Familiarity	Familiarity coefficient
Familiar with	1.0
Be familiar with	0.8
Familiar with	0.6
Commonly	0.4
Less familiar with	0.2
Very unfamiliar	1.0

Expert opinion coordination index

The degree of coordination of expert opinions is used to measure the degree of consistency between different experts' attitudes and opinions on the same issue. Usually, the higher the degree of agreement between different experts on the same issue, the closer the result is to the true level. The coordination coefficient is generally represented by the Kennell coefficient C. The value of C ranges from 0 to 1. The closer the value of C is to 1, the higher the recognition of the index system by experts and the more accurate the data results. The formula for calculating the Kennell coefficient C is as follows:

$$C = \frac{D_j}{E_j} \tag{3}$$

wherein,

$$D_j = \sqrt{\frac{\sum_{i=1}^{m_j} \left(d_{ij} - E_j\right)^2}{m_j - 1}} \tag{4}$$

$$E_j = \frac{\sum_{i=1}^{m_j} d_{ij}}{m_j} \tag{5}$$

In the formula, C is the degree of coordination of expert opinions, E_j is the arithmetic mean of the evaluation index j, and the value ranges from 0 to 100. m_j is the number of experts participating in the evaluation of the indicator j, d_{ij} is the score value of the i expert on the evaluation indicator j, and D_j is the standard deviation of the evaluation indicator j.

When the $A \geq 8.0$, $B \geq 5.0$ and $C \leq 8.0$ of the calculated indicators are selected as the evaluation indicator system.

According to the previous analysis, the reliability evaluation indicators of the transportation system are summarized into three categories, namely, the reliability indicators of connectivity, reliability indicators of travel time, and reliability indicators of smooth flow.

2.2 Evaluation Index Weight Calculation

The constructed reliability evaluation index system of smart transportation system needs to assign values to each indicator while clearly interpreting the meaning of each indicator, that is, to establish the weight of each indicator. Indicator weight refers to the proportion of each evaluation indicator in the comprehensive evaluation, which directly affects the results of the comprehensive evaluation. At present, the methods for determining the weight of indicators mainly include subjective weighting method, objective weighting method and combination of subjective and objective weighting method [8].

Subjective weighting method means that experts determine the weight of indicators according to their own experience and subjective judgment of the actual situation, including analytic hierarchy process (AHP), fuzzy evaluation method, binomial coefficient method, etc. The subjective empowerment method is a reflection of the will of the decision makers. Due to the different degrees of subjective cognition of the importance of the various indicators, the decision makers will inevitably have a certain degree of subjective arbitrariness. Sometimes different variables are given the same weight. For example, the Human Development Index is the arithmetic mean of three indicators, including life cycle per capita, education, and GDP. The basis of the subjective weighting method is that the expert must be very familiar with the research object. If this condition is not met for some reason, the evaluation results given will be biased. The objective weighting method is based on an objective weighting criterion determined in advance, and then provides information from the sample of the research object, and calculates the weight by mathematical or statistical methods. That is, the method of obtaining the weight by mathematically processing the original information of each index, including the coefficient of variation method, the entropy value method, the factor analysis method, the principal component analysis method, and the multi-objective programming method. The objective weighting method excludes most of the subjective components, and the results are generally "neutral". However, the objective weighting method is always the optimal solution under a certain criterion. If only considering its "optimal" mathematically, there will be unreasonable results.

In order to consider the subjective cognition experience of decision makers on the importance of indicators, and at the same time take into account the objective information of each indicator itself, the subjective and objective combination weight assignment method has become a trend. Based on the optimization theory, it builds an optimization model of the comprehensive weight of indicators and obtains the exact solution of the model, which improves the shortcomings of the single weighting method to a certain extent. When combining subjective and objective integration to empower, different integration methods can be adopted according to different goals. It can be based on the largest comprehensive evaluation target value, or based on the largest deviation from the negative ideal, or based on the smallest deviation of the decision result under subjective and objective weighting, or even based on the smallest sum of squared deviations between the subjective and objective weights [9]. Based on the above analysis, the AHP method and factor analysis method are used to calculate the comprehensive weight of the indicators.

(1) **Analytic hierarchy process**

Subjective weight determination based on the Analytic Hierarchy Process (AHP) method. AHP is a widely used method for determining subjective weights. When using the AHP method to determine the subjective weight of the indicators, firstly, the hierarchical structure model between the target layer and the criterion layer is established, and the judgment matrix between the relevant factors at each level is constructed according to the data and experts according to the scaling method. Then, the single-level ranking and the total-level ranking of each level are obtained, and then the consistency test is carried out on the judgment matrix of each level. When the ratio CR of the consistency index CI and the average random consistency index RI is less than 0.1, the judgment matrix has satisfactory consistency. Finally, the maximum eigenroot and weight vector of the matrix are obtained by the sum-product method.

(2) Factor analysis method

Factor analysis is a method to simplify data processing and problem analysis. It can describe and express the information that contains almost all the data by means of dimensionality reduction with few indicators. These representative indicators are calculated by certain mathematical models. Moreover, in the subsequent analysis, it is necessary to consider the proportion of each main factor to calculate the comprehensive score of the factors, and the weights in the factor analysis method are also calculated and processed with the help of mathematical models and SPSS. Therefore, the disadvantage of artificially defining the proportion of factors is avoided, and the interference of human factors is eliminated, so that the results of factor analysis have higher objectivity, and the distorted part is reduced.

The calculation process of the comprehensive weight of the indicators is shown in Fig. 1.

The formula for determining the comprehensive weight is as follows:

$$W_j = pV_{1j} + (1 - p)V_{2j} \tag{6}$$

In the formula, W_j is the comprehensive weight of the j index, V_{1j} is the weight value of the j index obtained by the AHP, V_{2j} is the weight value of the j index obtained by the factor analysis method, and p is the subjective preference coefficient. The function is established for the purpose of minimizing the sum of squared deviations of subjective weights, objective weights and combined weights:

$$\min\ Y = \sum_{i=1}^{n} \left(W_j - V_{1j}\right)^2 + \left(W_j - V_{2j}\right)^2 \tag{7}$$

In the formula, min Y is the minimum sum of square deviations of subjective weight, objective weight and combined weight.

The formula (6) is brought into the above formula (7), the subjective preference coefficient p is solved, and the complete formula for determining the comprehensive weight is obtained.

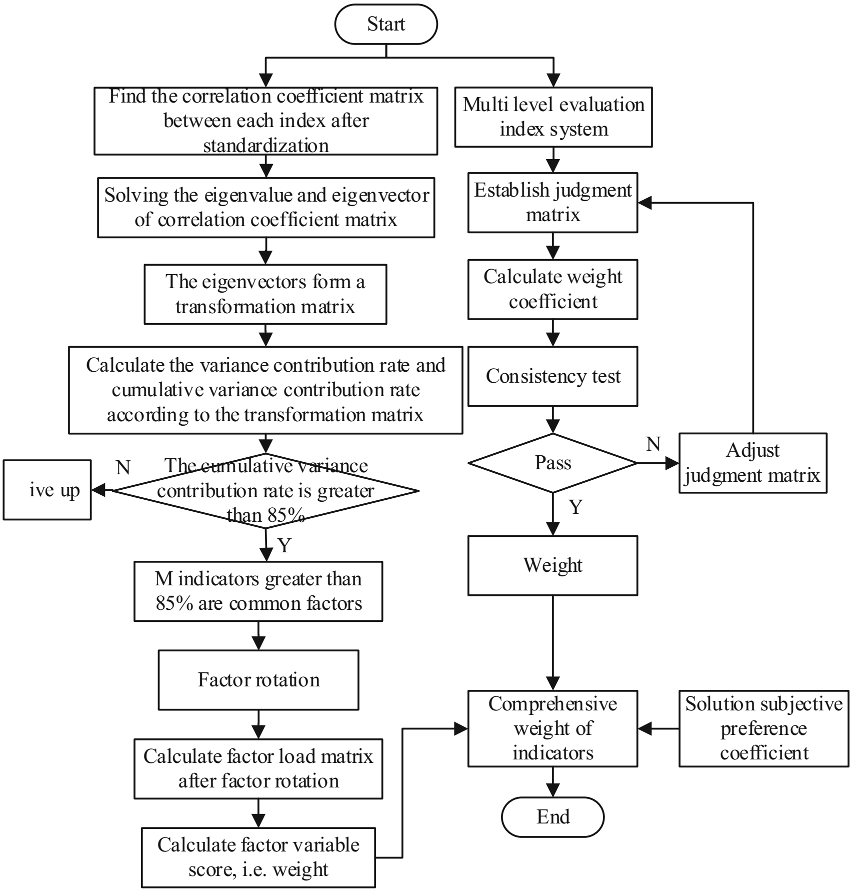

Fig. 1. The calculation process of the comprehensive weight of indicators

2.3 Evaluation Model Based on Deep Learning

Deep learning is a research direction gradually formed with the continuous development of artificial neural networks. As a special machine learning technology under development, deep learning is still limited in academic circles, so there is no unified definition. Deep learning is a data-driven modeling method, which can be regarded as a machine learning method that performs unsupervised or semi-supervised feature extraction through multi-layer nonlinear information processing units to achieve classification and prediction. Deep learning uses algorithms to parse labeled training samples and learn some potential patterns from the samples. Then, the complex data relationship is modeled, and the model is used to analyze and predict the samples, so as to better complete the required tasks [10, 11]. The core idea of deep learning is to establish a multi-level learning process, simulate the human brain for analysis, learning and induction, and use the mechanism of the human brain to analyze data and solve problems.

The vigorous development of deep neural networks solves the problem of insufficient representation ability of shallow network functions. In addition, the deep neural network solves the gradient disappearance phenomenon that occurs in the traditional neural network with the increase of the number of network layers. Therefore, it will be the next development direction to introduce the reliability evaluation model of intelligent transportation system in combination with deep learning theory. This chapter takes deep learning as the basic theory and the deep belief network as the theoretical support of the evaluation model, and completes the reliability evaluation of the intelligent transportation system from the perspective of deep learning.

Using deep learning mode to perform TSA work is actually a process of learning and classification. By learning a large amount of data containing feature information to improve the evaluation model, the model can obtain the ability of accurate classification. From the perspective of deep learning, a complete deep belief network evaluation model includes feature information extraction function and classification function. The hidden layer of feature extraction is composed of multi-layer restricted Boltzmann machines in the form of stacking, and the feature information processing layer with classification ability constitutes a complete evaluation model. Because the Boltzmann machine (BM) has advantages in data processing, it is time-consuming in the model training process. Therefore, in order to make up for its own shortcomings while retaining its advantages, some experts and scholars have proposed Restricted Boltzmann Machines (RBM). RBM is a two-layer network model, namely visible layer and hidden layer. Compared with M, the biggest advantage of RBM lies in its symmetrical network structure and the connection method of nodes between layers. This advantage is mainly manifested as follows:

(1) Since each neuron node in the hidden unit is independent of each other and only connected to the visual unit, the hidden unit can be determined by the value of the visual unit node, which will improve the efficiency of calculating the expected value;
(2) Similarly, since the nodes of the visible unit are also independent of each other, the state of the nodes in the hidden unit can be obtained from the input data through Markov chain sampling, so that the independent expected value can be obtained.

DBN is composed of multiple RBMs stacked with certain rules. In this model, the visual unit is responsible for receiving input sample data, the hidden unit is responsible for feature information extraction, and the label layer is responsible for outputting the classification results. The number of visible element nodes and the number of label layer nodes are determined by the dimension of the input data and the number of categories of the classification, respectively. The composition process of the evaluation model based on the DBN network is as follows:

Step 1: Input feature selection. The intelligent transportation system will have a large amount of indicator data information during operation, and these data will reflect the reliability of the system to some extent. For the specific process, please refer to Sect. 1.1 Research.
Step 2: First, collect the required data according to the index system, in order to improve the interaction between different features and avoid the failure of feature information to affect the experimental results. In this paper, the most commonly used normalization

method Min-Max is used to process the data, and its formula is as follows:

$$s' = \frac{s - s_{\min}}{s_{\max} - s_{\min}} \tag{8}$$

In the formula, s' represents the new feature information (index information) obtained by normalizing the input data, and s represents the original feature information, $s_{\max}$ represents the maximum value among all the selected feature information, and $s_{\min}$ represents the minimum value among all the selected feature information. The values of the feature information are all mapped in the 0–1 range after Min-Max normalization processing, which greatly reduces the difference between each feature information (indicator).

Step 3: Build 5 output nodes according to the categories of evaluation classification, representing high reliability, high reliability, general reliability, low reliability, and low reliability. They are represented by 10000, 01000, 00100, 00010, and 00001 respectively. The reliability of the intelligent transportation system is judged based on the reliability index, and its expression is as follows:

$$Q = \sum_{j=1}^{n} W_j \cdot s_j' \tag{9}$$

In the formula, Q represents the reliability index, W_j represents the comprehensive weight of the j indicator, s_j' represents the data of the j indicator, and n represents the number of indicators.

When $Q > 1.0$, the reliability of the intelligent transportation system is high;
When $0.8 < Q < 1.0$, the reliability of the smart transportation system is high;
When $0.6 < Q < 0.8$, the reliability of the intelligent transportation system is general;
When $0.4 < Q < 0.6$, the reliability of the smart transportation system is low;
When $0.0 < Q < 0.4$, the reliability of the smart transportation system is low;

Step 4: The obtained simulation data is randomly divided into three parts in proportion, w1hich are the unlabeled sample data for pre-training, the labeled sample data for parameter fine-tuning, and the test sample data for detecting and evaluating the model.

Step 5: Pre-training stage: The obtained unlabeled training samples are input into the evaluation model, and the model starts from the bottom layer for layer-by-layer training, and the two adjacent layers are an RBM.

Step 6: Parameter fine-tuning stage: After the model completes pre-training, the sample data is used as input, and the label information corresponding to each data is used as the expected output of the model. Using the loss function and gradient descent principles, the parameters of the model are fine-tuned until the specified number of iterations are completed.

After the above process, the research on reliability evaluation of intelligent transportation system based on deep learning is completed.

3 Evaluation Method Testing and Analysis

3.1 Research Object and Background

In order to verify the validity of the reliability evaluation method of intelligent transportation system based on deep learning. The main urban area of a city includes 9 administrative regions, covering an area of 5,473 square kilometers, and the urban construction land area is 595.03 square kilometers, an increase of 25.8 square kilometers and an increase of 4.5070 over the same period last year. Among them, the urban road land was 107.73 square kilometers, an increase of 7.1 square kilometers over the same period of last year. The resident population of the main urban area is 8.518 million, a year-on-year increase of 2.0070, making it one of the typical large cities. The city uses the smart transportation system for traffic scheduling and management in 9 administrative regions, testing the application performance of the evaluation method.

3.2 Evaluation Index System

According to the score given by each expert, the positive coefficient, authority coefficient and coordination coefficient of each evaluation index are calculated, and the results are shown in Fig. 2.

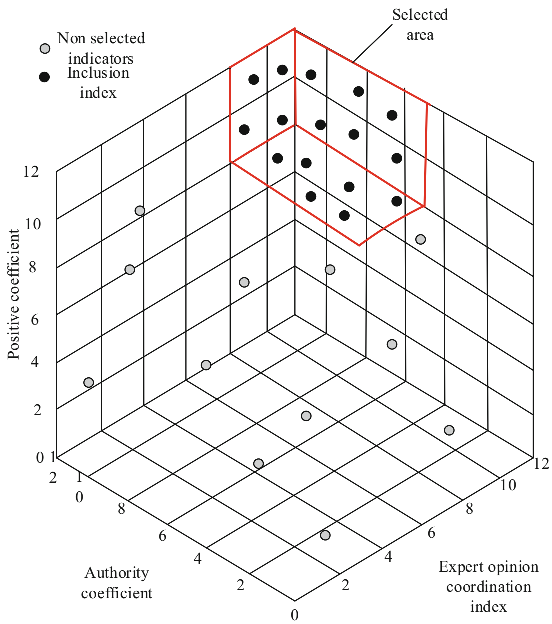

Fig. 2. Selection of evaluation indicators

Based on Fig. 2, a total of 16 indicators were selected, and an evaluation indicator system was established as shown in Table 3.

Table 3. Evaluation index system

Level I indicators	Level II indicators	Level III indicators
Reliability of intelligent transportation system	System travel time reliability	Travel time index
		Delay time index
		Buffer time index
		Tolerable time boundary
	Smooth system reliability	Travel speed index
		Road network unit saturation
		Proportion of unimpeded mileage
		Clear duration
	System connectivity reliability	Road network density
		Non linear coefficient
		Proportion of broken roads
		Road grading index

3.3 Comprehensive Weight of Evaluation Indicators

The AHP method and factor analysis method were used to calculate the comprehensive weight of the indicators. Taking three areas as an example, the comprehensive weights of evaluation indicators are obtained as shown in Fig. 3 and Table 4.

3.4 Reliability Analysis

Calculate the reliability index of the intelligent transportation system and judge its reliability. The results are shown in Fig. 4.

It can be seen from Fig. 4 that the intelligent transportation system is applied in 9 different administrative regions, and the obtained reliability indices are all above 1.0, indicating that the reliability of the intelligent transportation system is high.

Taking the above reliability index as the index, the reliability of the proposed method and the method of reference [3] is tested by five groups of experiments. The test results are shown in Fig. 5.

It can be seen from Fig. 5 that the reliability of the method of reference [3] is about 0.8, while the reliability of the proposed method is always higher than 1.0, which proves that the proposed method has good evaluation effect.

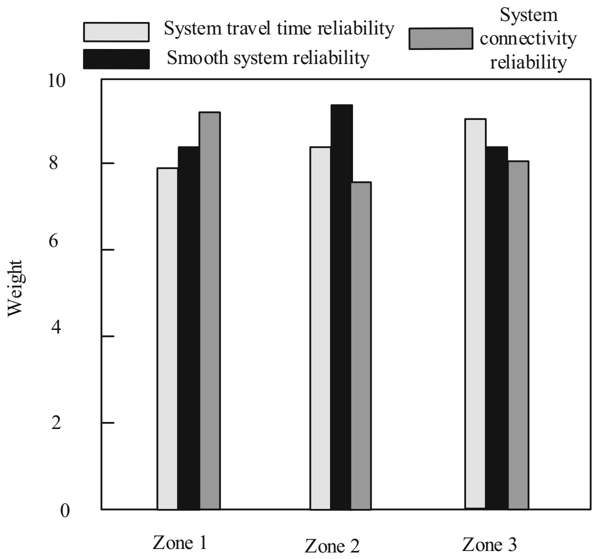

Fig. 3. Comprehensive weights of secondary indicators

Table 4. Comprehensive weights of three-level indicators

Level III indicators	Zone 1	Zone 2	Zone 3
Travel time index	2.53	1.21	2.52
Delay time index	1.824	0.87	1.54
Buffer time index	4.23	1.25	2.41
Tolerable time boundary	2.201	2.62	2.22
Travel speed index	1.52	2.88	2.88
Road network unit saturation	1.22	2.47	2.62
Proportion of unimpeded mileage	5.21	2.32	4.74
Clear duration	4.12	5.21	4.44
Road network density	4.47	4.12	3.65
Non linear coefficient	6.32	2.55	2.54
Proportion of broken roads	6.85	2.36	4.12
Road grading index	5.23	3.33	2.55

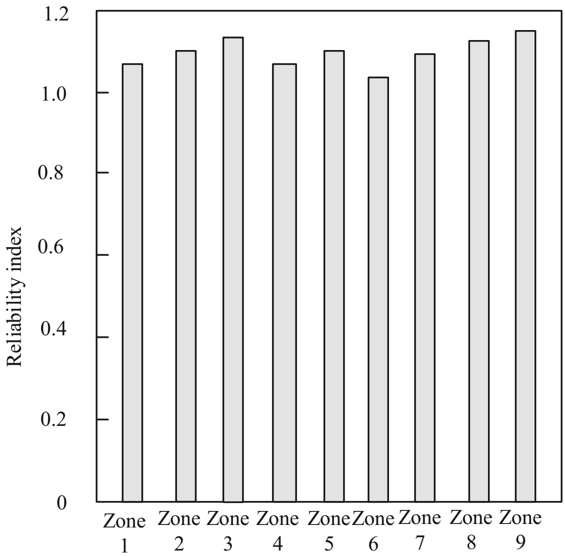

Fig. 4. Reliability index

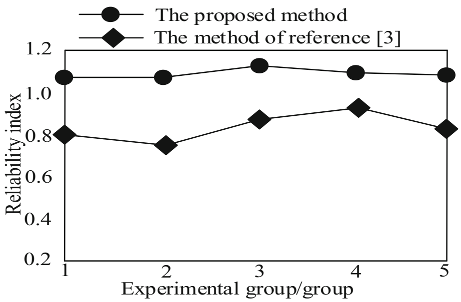

Fig. 5. Reliability test

4 Conclusion

The smart transportation system is the lifeblood of urban development and the core to ensure the normal operation of the city. A stable, efficient and reliable smart transportation system is not only the basis for travelers to achieve their travel goals, but also the ultimate goal of urban traffic management and planners. To this end, a reliability evaluation method of intelligent transportation system based on deep learning is proposed. The following achievements are made: the intelligent transportation system is applied to different areas, and the system reliability is high, which proves the effectiveness of the method. It can maximize the rational allocation of existing resources and effectively explore the potential of the road network, which has great theoretical significance and application value for improving the level of urban traffic management and dealing with the hazards caused by sudden disasters and emergencies.

In order to improve the accuracy of the system reliability analysis and evaluation results, the sensitivity of various indicators to reflect the actual situation, the degree of deviation of the indicators from the actual situation in the long-term change trend, and the relevant theories and practices at home and abroad should be taken into consideration in the future research, so as to put forward more in-depth and meaningful suggestions for improving the reliability of the transportation system in the central area of large cities.

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