Intelligent Transportation and Smart Cities
V. Mezhuyev et al. (Eds.)

doi:10.3233/ATDE250238

Dynamic Resilience Assessment of Urban Traffic Systems Based on Integrated Deep Learning

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Abstract. The resilience of urban transportation system is an important basis for building a resilient city. The existing assessment methods are faced with the challenges of complex influencing factors, difficult quantification of resilience index and low accuracy of traditional single model. In order to solve these problems, this study proposes a dynamic resilience evaluation method of urban transportation system based on deep learning model. This method constructs a resilience assessment model of urban transportation system, quantifies and integrates dynamic influencing factors. Convolutional neural network (CNN) was used to extract the dynamic characteristics of the toughness index, combined with Bidirectional Gated Recurrent Unit (BiGRU) to explore the time correlation, and the attention mechanism was used to enhance the important features. Taking Zhengzhou metropolitan area as an example, the empirical analysis found that the overall resilience of the urban transportation system in this region was at a medium to high level and showed a slow rising trend (resilience index increased from 0.319 in 2013 to 0.347 in 2022, with an average annual growth rate of 8.611%). However, there are significant differences in resilience levels among cities within the region (Zhengzhou has the highest annual mean resilience index (0.802) and Pingdingshan has the lowest (0.105). Compared with the traditional model, the model shows better performance in terms of mean absolute percentage error (MAPE = 0.06275%), root mean square error (RMSE = 0.018698%) and coefficient of determination (R^2= 0.9912), which verifies the validity and reliability of the model.

Keywords. Urban traffic, system resilience, convolutional neural network, bidirectional gated recurrent unit, attention mechanism

1. Introduction

As an important part of urban lifeline, the resilience level of urban transportation system is directly related to the anti-interference ability, adaptive recovery ability and sustainable development ability of the city in emergencies [1]. How to build a scientific, dynamic and accurate resilience assessment system has become the core issue of common concern in academia and engineering.

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Current studies on the resilience assessment of urban traffic systems present interdisciplinary characteristics. Scholars mainly conduct studies from the dimensions of network topology [2], dynamic performance function [3], analytic hierarchy process [4], dynamic Bayesian network [5], and resilience under cascade failure scenarios [6]. The current resilience assessment ignores the function of the transportation network and lacks dynamic spatiotemporal analysis [7]. The traditional model generally faces three limitations: First, the static index system is difficult to characterize the spatio-temporal dynamic coupling characteristics of resilience factors; Second, the nonlinear mechanism of system evolution can not be analyzed by single modal analysis method. Third, the ability of reasoning logic and data-driven collaborative decision-making is insufficient. At the same time, deep learning technology has been successfully applied in traffic flow prediction [8], congestion propagation modeling [9], road network optimization [10] and other scenarios. Machine learning is an effective method for studying resilience assessment in the future [11], but its application in dynamic assessment of urban traffic resilience is still in the exploration stage. In particular, there are shortcomings in multi-scale spatio-temporal feature fusion and key event attention allocation.

Aiming at the above problems, this paper proposes a dynamic assessment method of urban traffic system resilience based on integrated deep learning model (Convolutional neural network-Bidirectional Gated Recurrent Unit-Attention, CNN-BiGRU-Attention), whose innovation and contribution are reflected in the following three aspects:

1) Model architecture innovation: For the first time, CNN (Convolutional neural network) and BiGRU (Bidirectional Gated Recurrent Unit) are deeply integrated with attention mechanism, and collaborative optimization of multi-dimensional resilience indicators is realized through spatial feature extraction, bidirectional time series dependence analysis and adaptive weight allocation.

2) Method breakthrough: A CNN-BiGRU-Attention fusion model was proposed to extract the spatial correlation features of multi-dimensional indicators through convolutional neural network (CNN), analyze the temporal evolution rule combined with bidirectional gated cycle unit (BiGRU), and introduce the Attention mechanism to focus on key disturbance events. A time-space coupling resilience evaluation method is developed.

3) Application value: Taking Zhengzhou metropolitan area as the empirical object, this paper reveals the spatio-temporal evolution law of regional urban traffic resilience, and provides data support for the formulation of differentiated inter-city traffic resilience improvement strategies.

2. Research Status

2.1. Urban Traffic Resilience Assessment Methods

The prediction and accurate assessment of the resilience of the traffic network is crucial for traffic management and emergency management [12]. At present, the commonly used quantitative evaluation methods of urban traffic resilience are index-driven, model-driven and data-driven, etc. Research on traffic resilience evaluation index methods can be roughly divided into network topology index evaluation, resilience characteristic index evaluation and resilience performance index evaluation [13]. Model-driven methods rely on mathematical modeling and simulation tools (such as SUMO and system dynamics) to simulate the evolution law of traffic flow under extreme events [14]. A combination of knowledge base and data-driven method is used for quantitative analysis of resilience [15]. In addition, some studies have incorporated time and performance into the indicators of resilience assessment of urban transportation systems [16].

2.2. The Application of Deep Learning Techniques

The application of deep learning in the field of transportation has become the core direction of intelligent transportation system research in recent years, which significantly improves the intelligence level of traffic prediction, monitoring, management and automatic driving scenarios by processing complex spatiotemporal data and mining nonlinear relationships. Bullard proposed a deep learning based road shoulder width identification and classification method, which used open source data and models to classify the road shoulder width, reducing the cost of road safety audit [17]. Delmo proposed a deep learning-based vehicle speed evaluation model in two-way traffic and conducted a case study, and the results showed that the model performed well in improving real-time target detection and speed estimation [18]. Fan proposed a deep reinforcement learning (DRL) framework to optimize emergency path planning through adaptive simulation of disaster scenarios and significantly shorten system recovery time [19]. Khan proposed an intelligent transportation framework for distributed machine learning to predict traffic in large-scale and dynamically evolving traffic scenarios. This method not only protects user privacy, but also reduces the difficulty of centralized neural network training, reduces communication delay, reduces data transmission volume, and improves the overall data processing efficiency [20].

3. Research Method

3.1. Model Design Goal and Innovation

Aiming at the shortcomings of existing resilience assessment methods, this paper proposes a fusion deep learning model based on CNN-BiGRU-Attention, which is designed specifically for the complexity and dynamics of resilience assessment of urban transportation systems. Its core objectives are as follows: the innovative value of the CNN-Bigru-attention model proposed in this paper. Compared with the traditional timing model, the architecture extracts spatial features through CNN, BiGRU captures bidirectional timing dependence, focuses on key influencing factors of Attention mechanism, and forms a spatio-temporal coupled resilience assessment.

Improvement Points: Compared with traditional models (such as CNN-LSTM or single-attention mechanism), this framework innovates in the following three aspects:

Bidirectional timing modeling: BiGRU captures both forward and reverse timing dependencies to solve the problem of insufficient analysis of long-term causal association by LSTM-class models [21].

CNN-BiGRU collaboration: The CNN layer extracts spatial features (such as road network density and multipath connectivity) and retains local spatial correlation. The BiGRU layer resolves both forward (influence of historical events) and backward (potential association of future events) timing dependencies through bidirectional gated units simultaneously.

Attention mechanism: Dynamic weight allocation: The Softmax function adaptively focuses on high-impact indicators and repress low-contribution features.

3.2. CNN-BiGRU-ATTENTION Resilience Evaluation Model

This model integrates convolutional neural network (CNN), bidirectional gated loop unit (BiGRU) and ATTENTION mechanism to form a multi-level and multi-dimensional deep learning framework, as shown in Figure 1, including five parts: input layer, CNN layer, BiGRU layer, ATTENTION layer and output layer.

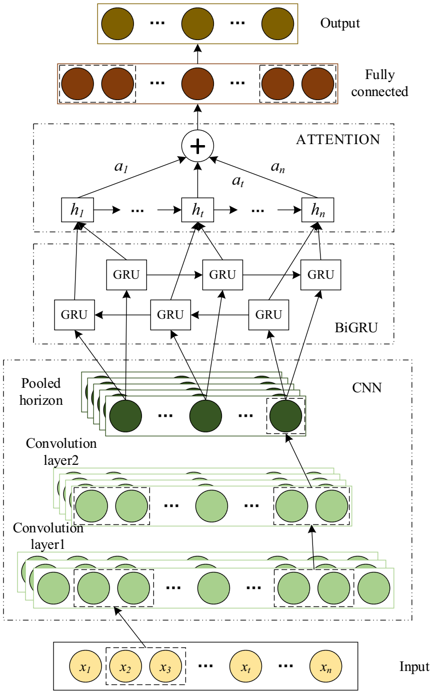

Figure 1. CNN-BiGRU-ATTENTION model structure.

(1) Input layer. The input feature vector is composed of static data (such as road network density, multipath connectivity rate) and dynamic operation data (real-time flow, emergency response time) of urban traffic infrastructure, including 23 standardized indicators. The data were normalized (Min-Max normalization) to eliminate dimensional differences and interpolated to fill in missing values to ensure the integrity and consistency of the input matrix.

(2) CNN layer. The CNN layer consists of two convolution layers and one pooling layer. In the first convolution layer, the number of convolution cores is 32, the activation function is ReLU, and the basic spatial patterns (such as regional road network density distribution) are extracted. The number of convolutional cores in the second layer is 64, and complex spatial features (such as multipath redundancy and hub node connectivity) are deeply mined. The pooling layer adopts the maximum pooling mode, the pooling size is 2, and the step size is 1. While retaining data fluctuation characteristics, dimensionality is reduced to avoid excessive smoothing of information.

(3) BiGRU layer. BiGRU layer receives 64-dimensional feature vectors of CNN output, and each layer is equipped with 20 neurons to balance computational efficiency and feature capture ability. The forward GRU captures the impact of historical events on the current state (such as the cumulative effect of investment policies), and the reverse

GRU analyzes potential future associations (such as traffic flow predictions), and the output is a weighted fusion of bidirectional hidden states.

(4) ATTENTION layer. By assigning different weights to the output feature vectors of BiGRU layer, key features were identified. The weight of high-impact indicators was significantly increased (accounting for 23.6%), and the redundancy feature rejection rate was > 67%, which enhanced the sensitivity of the model to sudden disturbances.

(5) Output layer. The output of the ATTENTION layer was calculated through the fully connected layer. The number of neurons in the fully connected layer was set to 20, and the activation function was Sigmoid. The output value was constrained to the interval 0,1, and the resilience level of the system was quantitatively characterized.

3.3. Evaluation Index of Resilience Assessment Model

To verify the validity of the resilience evaluation model, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and the coefficient of determination (R-square, R2) are selected to assess the accuracy of the evaluation model. MAPE quantifies the real situation of the deviation of the evaluation value, and RMSE represents the deviation between the evaluation value and the real value. The smaller the value of the two values, the higher the evaluation accuracy. R2 reflects the advantages and disadvantages of the evaluation model, with a numerical value range of [0, 1]. The closer it is to 1, the better the performance of the evaluation model is. MAPE and RMSE and R2 are calculated as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i' - y_i}{y_i}\right| \times 100\% \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i' - y_i)^2}{\sum_{i=1}^{n}(\bar{y}_i - y_i)^2} \tag{3}$$

In the formula, y_i represents the true value of the i value after the resilience values of all urban traffic in all years are ranked in order, y_i' represents the estimated value of the i value, $\bar{y}_i$ represents the mean value, and n is the total number of values.

4. Case Study

4.1. Area Description

The study area is Zhengzhou metropolitan area, which consists of 9 cities including Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Xinxiang, Jiaozuo, Xuchang, Luohe and Jiyuan. These nine cities are closely related to social exchanges and economic development, forming Zhengzhou metropolitan area with a total area of 58,800 km2 and a resident population of 46.7 million. According to the national planning, the development pattern of “one core, one pair, one belt and multiple points” has been constructed. By November 2023, the comprehensive transportation network of Zhengzhou metropolitan area has reached 103,000 km.

4.2. Selection of Influencing Factors of Resilience

This paper analyzes the safety resilience of urban transportation system, starting from the macro dimension of the overall capacity of urban transportation system and considering the resilience of urban transportation system in terms of characteristic indicators. By analyzing the various components of urban transportation system and their cooperative operation characteristics, and fully considering the related performances of each network layer that may affect the resilience of urban transportation system, the influencing factors of urban transportation system resilience are divided into three categories and six stages according to the event development process. In addition, combined with expert consultation and investigation of site construction logs, the six subsystems of urban transportation network system are analyzed. The main characteristic indexes affecting the resilience of the subsystems are screened out, and the specific influencing factors in each subsystem are obtained. In terms of actual variables, 23 kinds of variable factors are collected from the real faults recorded in the field construction logs, which are divided into 8 categories for convenience of analysis. In addition, four variables related to organization and management were collected through expert consultation.Results and discussion

4.3. Result Analysis

After using the digital twin and entropy method to process the index data that affect the resilience of the urban transportation system, the obtained data is divided into training set and test set, and the CNN-BiGRU-Attention model is trained, and then the test set is used to verify the training results. Finally, the resilience index of urban traffic system generated by CNN-BiGRU-Attention model is obtained.

The overall resilience index of Zhengzhou metropolitan area is shown in Table 1. The overall development of Zhengzhou metropolitan area was relatively stable from 2013 to 2022, with a downward trend from 2013 to 2017, decreasing from 0.319 in 2013 to 0.277 in 2017. From 2017 to 2019, it showed an upward trend, increasing from 0.277 in 2017 to 0.309 in 2019. From 2019 to 2022, it first decreased and then increased. Combined with Table 1, it can be seen that in the past ten years, the overall resilience index of Zhengzhou metropolitan area has been at Grade III for four years and at Grade IV for six years. On the whole, the overall resilience of urban transportation infrastructure in Zhengzhou metropolitan area has remained at a medium-high level in the past ten years.

Table 1. Overall resilience index of Zhengzhou metropolitan area.

Year	Resilience index
2013	0.319333
2014	0.319333
2015	0.304272
2016	0.277294
2017	0.277282
2018	0.291748
2019	0.309311
2020	0.307954
2021	0.323757
2022	0.346831

The development trend of urban transportation system resilience in Zhengzhou metropolitan area is shown in Figure 2. It can be seen that Zhengzhou holds the leading position in the urban traffic resilience index of the Zhengzhou metropolitan area, which is related to the urban traffic infrastructure construction and capital investment in

Zhengzhou in recent ten years. Zhengzhou, as the capital of Henan Province, has a road network density of 6.8 km/km2, which is higher than the average value of metropolitan area (4.2 km/km2). Additionally, the multi-path connectivity rate in key areas reaches 92%. Compared with Pingdingshan (multi-path connectivity rate is 47%), the road network redundancy of Zhengzhou is significantly improved ($\Delta = 45\%$), which verifies the positive impact of investment scale on resilience. Furthermore, due to the relatively perfect communication facilities Zhengzhou also has a strong emergency response capability. However, in recent years, the resilience index of urban transportation system in Zhengzhou has declined due to the decrease in capital investment in urban transportation infrastructure and the decrease in per capita road area caused by the increase of resident population in Zhengzhou.

The urban traffic resilience index of Jiyuan City and Luoyang City over the past ten years has been in the second echelon, and the overall trend first declines and then rises. Luoyang's economic development level consistently ranks second in the province all the year round, second only to Zhengzhou. It can be seen that the level of economic development and the investment in urban transportation infrastructure construction have an obvious influence on urban transportation resilience.

The remaining six prefecture-level cities are in the third echelon. In recent years, the urban area of these city has been expanding, the number of permanent residents has been increasing, and the travel demands of residents are also increasing. Thanks to the continuous improvement of urban transportation infrastructure, including the increase in road areas, the establishment of various rapid transportation connection systems and the improvement of transportation service quality in prefecture-level cities, the overall level of urban transportation system resilience has steadily increased.

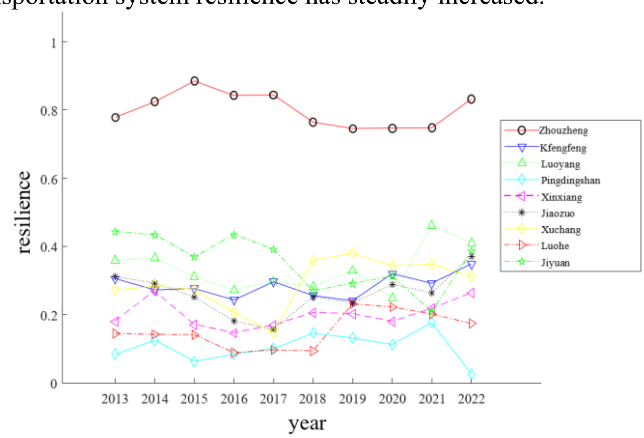

Figure 2. Change trend of resilience development level of urban transport system in Zhengzhou Metropolitan area from 2013 to 2022.

4.4. Comparison of Model Evaluation Results

In order to verify the advantages of CNN-BiGRU-ATTENTION model in urban transportation system resilience evaluation, other models are trained together with the model in this paper. After testing with the test set, three evaluation indexes, MAPE, RMSE and R2, are used to compare the performance of the models. The comparison results are shown in Table 2.

Table 2. Comparison of model prediction results.

Model	MAPE	RMSE	R2
BP	0.14403	0.041996	0.955588
CNN	0.119088	0.035455	0.968345
CNN-LSTM	0.094238	0.028436	0.979637
CNN-BiGRU-ATTENTION	0.06275	0.018698	0.9912

It can be seen from Table 2 that the MAPE, RMSE and R^2 indexes of CNN-BiGRU-ATTENTION model are 0.06275%, 0.018698% and 0.9912 respectively. Compared with BP neural network, CNN and CNN-LSTM model, the MAPE of CNN-BiGRU-ATTENTION model proposed in this paper is reduced by 0.08128%, 0.056338% and 0.031488%; RMSE decreased by 0.023298%, 0.016757% and 0.009738%, and the two indexes were the lowest among the four models; R^2 increased by 0.03561, 0.02286, and 0.01156, making it the highest among the four models. It can be seen that CNN-BiGRU-ATTENTION model is superior in model accuracy and performance compared with other models.

The comparison between the evaluation results of different models and the real values are shown in Figure 3. The differences between different models can be seen more intuitively from the Figure 3. Compared with other models, the CNN-BiGRU-ATTENTION model can better fit the real resilience curve of urban transportation system.

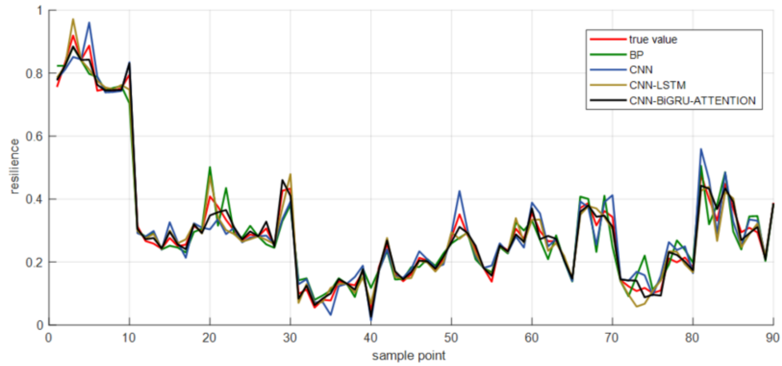

Figure 3. Comparison of different models.

5. Conclusions

In this paper, the CNN-BiGRU-ATTENTION model is used to intelligently evaluate the urban traffic resilience of Zhengzhou metropolitan area, and the following conclusions are drawn:

(1) This paper analyzes the safety resilience of the urban transportation system, starting from the macro dimension of the overall capacity of urban transportation system. Combining with the methods of expert consultation and site construction log investigations, and screening out 8 categories of 23 variable factors to comprehensively evaluate the resilience of urban transportation.

(2) CNN-BiGRU-Attention model demonstrates significant advantages in urban transportation system resilience evaluation by integrating spatio-temporal feature extraction and attention mechanisms. Its innovation lies in the ability to perform multi-modal feature extraction, spatio-temporal feature fusion and refined evaluation. By multi-modal feature fusion and dynamic weight distribution, the model can capture the

complexity and dynamics of the system more comprehensively. this provides new ideas and methods for research in related fields.

(3) The resilience of the overall urban transportation system in Zhengzhou metropolitan area is at a medium-high level and develops steadily. Among the influencing factors affecting the resilience of urban transportation system, the annual investment in transportation infrastructure, the maintenance cost of transportation infrastructure and the total investment in smart technology research and development have the highest influence degree, indicating that the resilience of urban transportation system depends on the construction of urban transportation infrastructure.

(4) The application of deep learning in transportation has expanded from single task to complex system-level optimization, but challenges in data, models, and real-world deployment still need to be addressed. The resilience assessment of urban transportation system based on deep learning requires a large amount of data as the premise of model construction, and a detailed understanding of urban transportation system. In the future, with the development of graph neural network, multi-modal fusion and edge computing technology, intelligent transportation system is expected to achieve a higher level of autonomous decision-making and collaborative management.

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