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Solving the Security Problem of Intelligent Transportation System With Deep Learning

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***Abstract*— Objective: the objective of this study is to study deep learning to solve the safety problems of intelligent transportation system. Method: the intelligent transportation system is improved by using the deep learning algorithm, and the improved system is simulated, and the data transmission performance, accuracy prediction performance and path change strategy of the system are statistically analyzed. Results: in the analysis of the data transmission performance of the system, the probability of successful propagation is found to be 100%. When the value of λ is 0.01∼0.05, it is the closest to the actual result and the data delay is the smallest. In the analysis of the accuracy prediction of the system, it is found that the system of this study has the best accuracy prediction performance with the increase of the number of iterations compared with other models in different categories. After further analyzing the path induction strategy of the system, it is found that the route guidance strategy of this study can effectively restrain the spread of congestion and achieve the effect of timely evacuation of traffic congestion in the face of congested road sections. Conclusion: it is found that the improvement of the intelligent transportation system by using deep learning can significantly reduce the data transmission delay of the system, improve the prediction accuracy, and effectively change the path in the face of congestion to suppress the congestion spread. Although there are some shortcomings in the experiment, it still provides experimental reference for the development of the transportation industry in the later stage.**

***Index Terms*— Intelligent transportation system, data transmission performance, deep learning, accuracy prediction, security.**

I. Introduction

WITH the acceleration of the process of social industrialization, people's living standards have improved, and clothing, food, housing and transportation have been greatly improved. Vehicles are issues that people must consider when traveling. In the current economic development of urban traffic congestion, the economic losses caused by traffic congestion cannot be estimated. This problem is not only in China, but also in developed cities around the world [1], [2]. Traffic congestion will not only cause personal inconvenience, but also cause environmental pollution due to vehicle exhaust emissions, which will lead to a decline in people's quality of life. Therefore, the design and application of intelligent transportation systems for monitoring traffic conditions have become the focus of research scholars.

Today, with the rapid development of science and technology, the intelligent process is accelerating. In transportation, many related intelligent transportation systems have also been developed. Intelligent Transportation System (ITS) usually refers to the integration of various advanced technologies, such as deep learning, big data, information and communication technology, wireless communication technology and electronic control, on the entire transportation management system. Computer technology and the Internet are fully applied in actual transportation [3]. Intelligent transportation system can not only collect the actual traffic conditions and vehicle related information, but also establish a wide range of real-time monitoring travel service mechanism in transportation [4]. For example, the on-board terminal system can record the current position, running time and running speed of the vehicle in real time, so as to respond to the objective state of the vehicle, but at the same time, it can also respond comprehensively and objectively to the current speed and fault of the vehicle. After the vehicle information is processed, it will be uploaded to the monitoring center by wireless technology for real-time monitoring, which also facilitates the monitoring center's real-time management of running vehicles [5].

Transportation system is a very complex transportation system. The traffic jam is not only caused by many cars, but also by other factors. The solution of traffic problems involves knowledge and methods of many disciplines, and the urban traffic problems have attracted great attention of our government [6]. After the neural network algorithm of deep learning is put forward, its application field develops rapidly and tends to be more intelligent. Like neurons in human body, its autonomous learning ability can extract important information from a large number of data and ignore minor and unimportant information to make intelligent discrimination on many kinds of information [7], [8]. In this way, the safety problems in travel, such as vehicle rear end, vehicle fault monitoring, information leakage and other issues will be greatly reduced.

Manuscript received November 21, 2019; revised January 27, 2020; accepted March 9, 2020. This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grant 61902203, in part by the Key Research and Development Plan-Major Scientific and Technological Innovation Projects of ShanDong Province under Grant 2019JZZY020101, and in part by the Technology and Innovation Commission of Shenzhen Municipality under Grant JCYJ20170412142239369. The Associate Editor for this article was A. Jolfaei. *(Corresponding author: Zhihan Lv.)*

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Digital Object Identifier 10.1109/TITS.2020.2980864

To sum up, although there are many researches on intelligent transportation system, there are not many researches on its safety. Therefore, in this study, deep learning algorithm is used to improve the previous intelligent transportation system. The improved system is simulated to make statistics and analysis of all aspects of the system performance, providing experimental reference for the later intelligent development of the transportation industry.

II. Literature Review

With the rapid development of science and technology, intelligence has become the trend of social development. In terms of transportation, intelligent transportation system is also gradually developed, which brings more convenience for people's travel. However, in real life, such as vehicle rear end, vehicle fault monitoring, information leakage and other issues are still frequent. In view of the further intelligent transportation system, many researchers have carried out relevant research.

A. Research Progress of Intelligent Transportation System

Intelligent transportation system is a kind of system developed for transportation. It combines big data and information communication technology effectively, which plays a very important role in transportation. Choi *et al.* (2016) evaluated the transfer assistance of the railway station and divided the train traffic movement into three stages: integrated transportation stage, transfer stage and shuttle stage. After analyzing the model of three stages, it is found that the bulk shipper is mainly in the stage of line transportation, and the stage of transshipment is also very important. In the subsequent railway freight policy, it is necessary to find the one that not only improves the competitiveness of the railway transport stage, but also improves the transfer stage of the railway station [9]. Wang *et al.* (2017) proposed a mobile congestion awareness system based on the traditional queuing time monitoring method for the current urban traffic conditions. This system can use sensor enhanced mobile devices and crowd intelligence to monitor and provide real-time queuing time information of various queuing scenarios. When people are waiting in a queue, the system can calculate the queuing time by using the acceleration sensor data and the environment for automatic detection, which is an effective method to predict the queuing state [10]. Based on the rapid growth of population at this stage, Gohar *et al.* (2018) proposed an intelligent system that can provide bus information to remote users in real time. The system tracks the bus in real time and then provides the information to remote users in real time. Moreover, the system can display the bus position in real time on Google map [11]. Chhaya *et al.* (2019) upgraded the original intelligent transportation system. On the basis of the original traditional display function, they also added many innovative functions, such as radio frequency identification (RFID) announcement, accident avoidance system, destruction of passenger ticket system, pollution control (PUC) system, automatic passenger counter (APC) and public safety function, which make the transportation system more intelligent [12].

B. Application Progress of Deep Learning in Intelligent Transportation System

With the rapid development of science and technology, the application of deep learning algorithm is more and more extensive, and the related research in transportation is also more and more. Li *et al.* put forward a set of algorithms that use deep reinforcement learning to design signal timing scheme. From the sampled traffic state and the corresponding traffic system performance output, the learning of Q function is strengthened. The appropriate signal timing strategy can be found through implicit modeling of control behavior and system state changes, and the implementation techniques are further described [13]. Ma *et al.* (2017) proposed a convolutional neural network (CNN) based method to learn the traffic volume as an image and predict the traffic speed in a large scale and network range with high accuracy. Through the two-dimensional space-time matrix, spatiotemporal traffic dynamics is transformed into an image describing the spatiotemporal relationship of traffic flow. Finally, it is found that the average accuracy of this method is improved by 42.91% in the acceptable execution time. Through the reasonable training of the model, it is found that it is suitable for large-scale traffic network [14]. Chand *et al.* (2018) analyzed the importance of passengers based on accurate and appropriate traffic related data, combined deep learning and Internet of things with intelligent transportation system, and further discussed the cluster control system, location identification and resource privacy in intelligent transportation system, bringing more convenience to people's travel [15]. Ferdowsi *et al.* (2019) explored an edge analysis architecture of intelligent transportation system, which processes data at the vehicle or roadside intelligent sensor level to overcome the delay and reliability challenges of intelligent transportation system. Finally, it is found that the system provides a reliable, safe and real intelligent transportation environment through the introduction of edge analysis architecture and the ability of deep learning algorithm [16]. In the same year, Li *et al.* proposed a deep feature fusion model to predict the spatial average velocity using heterogeneous data. In this model, the best fusion result can be obtained by extracting and training the original data, fusing the representative features and developing the correlation. Compared with the widely used data level fusion methods, the proposed depth feature fusion model can achieve better fusion results [17].

To sum up, there are many researches on intelligent transportation system, but there are not many researches on the application of deep learning to the safety of intelligent transportation system. Therefore, in this study, deep learning technology is applied to the intelligent transportation system to evaluate the safety performance of the system from many aspects.

III. Experiments and Methods

A. Deep Learning Algorithm

The concept of deep learning comes from the research of artificial neural network. As a new technology, this algorithm will be used to simulate and extend human intelligence.

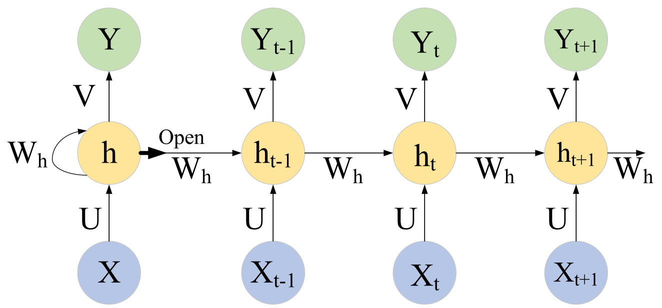

Fig. 1. Schematic diagram of cyclic neural network.

Its application in various fields has great challenges. Especially in the field of transportation, its importance cannot be ignored. In this study, the deep learning model of Gated Recurrent Unit (GRU) is mainly constructed. By introducing the principle of GRU neural network and the internal structure of neurons, the deep learning model is built [18]. GRU neural network belongs to cyclic neural network (RNN). Its structure is mainly divided into input layer, loop layer and output layer. The data sets of each layer are represented as $\{X_1, X_2, \ldots, X_t, X_{t+1}\}$, $\{H_1, H_2, \ldots, H_t, H_{t+1}\}$ and $\{Y_1, Y_2, \ldots, Y_t, Y_{t+1}\}$ respectively. The schematic diagram of the cyclic neural network is shown in figure 1.

From figure 1, it can be seen that the neurons in the same layer of input layer and output layer have no information association, while the neurons in the same layer of circulation layer have information association. The expression of the data relationship between loop layers is as follows:

$$H_t = f(U \cdot X_t + W \cdot h_{t-1}) \tag{1}$$

The relationship between the output layer and the loop layer is as equation (2):

$$Y_t = f(V \cdot h_t) \tag{2}$$

In equation (1) and (2), f ( ) is the activation function, U and V represent the weight matrix of input layer and loop layer, and output layer and loop layer respectively. Xt and Yt are the input and output values at time t, respectively. W is the weight matrix between neurons in the circulatory layer. Ht is the state matrix of the time t of the neurons in the circulatory layer. In the loop layer, the information of neurons at each time interacts with each other through the w-weight matrix. The value of h_t in the cycle layer neuron at time t is correlated with the input Xt at this time and h_{t-1} at the previous time, which shows that the cycle neural network can predict the next time according to the characteristics of the historical time series. In the cycle layer, the information of the current time is determined by the time step parameter, which is determined by the duration [19]. The inner structure of the neurons in the cycle layer of GRU neural network includes update gate and reset gate. Update gate is a combination of input gate and forgetting gate. The functions to update and reset gates are as follows:

$$Z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{3}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{4}$$

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{5}$$

In equations (3), (4) and (5), $\cdot$ represents the multiplication of the corresponding elements of the matrix. [A, B] refers to matrix connection. Wz, and Wr refer to the threshold weight of update door and reset door. Wh represents a temporary neuron state weight. Ht-1 is the neuron state value at the time of t − 1. x_t is the input value at time t. $\sigma(x)$ represents the sigmoid function. The purpose of update gate is to control the retention of neuron information. The larger the value is, the more information the neuron retains at the current time, and vice versa. Reset door is used to control the neglect of the previous moment. The larger the value is, the smaller the degree of neglect is. Otherwise, the greater the degree is [20]. The internal neuron structure of GRU neurons in this study is similar to that of long-term memory network (LSTM), but it has similar characteristics in speech recognition, natural language processing and so on, and it can ensure that gradient dissipation is avoided in the process of information back propagation. The most advantage is that it has certain advantages in learning convergence speed.

GRU neural network based on deep learning mainly uses Back propagation through time (BPTT). Data input methods include batch input, stochastic input and mini-batch input. In batch input, although the local optimal solution can be obtained, the calculation speed of gradient descent is slow. In the stochastic input, although it has an advantage in calculation speed, the accuracy of the final result is affected because of the large oscillation near the local optimal solution. In addition, in the mini-batch input, the advantages of batch input and stochastic input are combined, which is a very ideal gradient solution method [21, 22]. In the GRU neurons of this study, the parameters to be learned include Wr, Wz, $W_{h'}$, W_h, V, U, etc. The loss function at t-time t is:

$$E_t = \frac{1}{2}(y_t^l - y_t)^2 \tag{6}$$

In the equation, y_t^l represents the tag value at time t. After further analysis, the loss values of samples at all times are as follows:

$$E = \sum_{t=1}^{T} E_t \tag{7}$$

Taking the $W_{h'}$ parameter as an example, the small batch input method is used for gradient calculation. Other parameters are similar. First, the relevant decomposition weights of $W_{h'}$ are as follows:

$$W_{h'} = W_{h'x} + W_{h'h} \tag{8}$$

It is found that $W_{h'}$ is related to input weight and neuron state weight. The gradient of $W_{h'}$ is calculated as follows:

$$\frac{\partial E_t}{\partial W_{h'}} = \frac{\partial E_t}{\partial W_{h'x}} + \frac{\partial E_t}{\partial W_{h'h}} \tag{9}$$

The items in $W_{h'}$ gradient equation are further expanded as follows:

$$\frac{\partial E_t}{\partial W_{h'x}} = \delta_t x_t \tag{10}$$

$$\frac{\partial E_t}{\partial W_{h'h}} = \delta_t (r_t \cdot h_{t-1}) \tag{11}$$

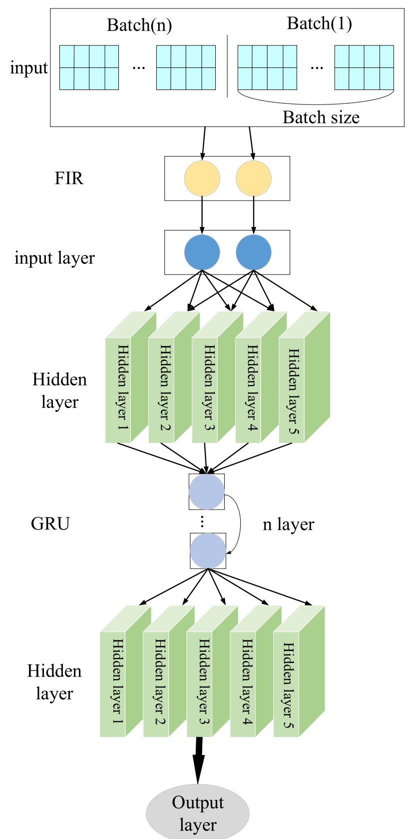

Fig. 2. Neural network model graph of deep learning algorithm.

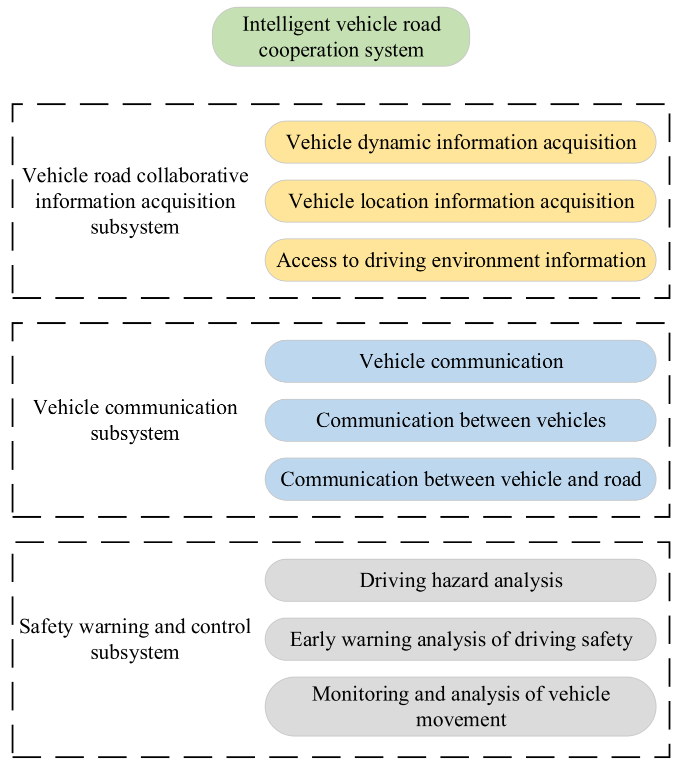

Fig. 3. Structure system diagram of intelligent vehicle road collaboration system.

δ_t refers to the error term, and equations (10) and (11) refer to the relevant hierarchical information difference relationship between the error term and each item. The error term is analyzed as follows:

$$\delta_t = f'(\delta_{h,t} \cdot z_t) \tag{12}$$

$$\begin{aligned}\delta_{h,t} &= \delta_{y,t} V + \delta_{z,t+1} W_{zh} + \delta_{t+1} W_{h'h} r_{t+1} \\ &\quad + \delta_{h,t+1} W_{rh} + \delta_{h,t+1}(1 - z_{1+t})\end{aligned} \tag{13}$$

$$\delta_{r,t} = h_{t-1}\sigma'\left(f'\left(\delta_{h,t} z_t\right) W_{h'h}\right) \tag{14}$$

$$\delta_{z,t} = \delta_{h,t}\sigma'\left(h'_t - h_{t-1}\right) \tag{15}$$

$$\delta_{y,t} = \sigma'\left(y^l_t - y_t\right) \tag{16}$$

The deep learning algorithm is further used to build the neural network framework, as shown in figure 2. Among them, time step refers to how many historical input values are used to predict future values. Learning rate refers to the learning step length in the gradient descent. When the data is input, it is divided into several batches by neural network. Each batch is subdivided in time steps. In the training process, if the learning rate is set too large, the loss value will oscillate near the local optimal solution. If it is too small, the convergence will be slow in the process of gradient descent. In this study, a linear adjusted learning rate method with gradient descent is defined [23].

B. Wireless Network

Wireless network exists in the network by the way of wireless energy transmission. Since Nikola Tesla's theory that two points can transfer energy freely without physical connection, its influence has been profound [24]. When the information is transmitted in the actual wireless network, the sensor nodes usually can only obtain the limited capacity of battery power, and it is difficult to make up or replace the power through the traditional way. Therefore, in wireless network, the core problem is how to achieve the high efficiency of energy consumption. In a dynamic resource scheduling mechanism, the sensor network based on energy collection can dynamically adjust the source coding rate to select the most valuable packets for transmission [25]. In the process of packet selection, the problem of packet selection can be described under the constraints of energy consumption and reliability in each time slot.

C. Intelligent Transportation System

Intelligent transportation system is a comprehensive transportation system which combines the advanced information technology, data communication technology, sensor technology, automatic control theory and artificial intelligence, and is used in transportation to provide people with safety, efficiency and energy saving travel [26]. The intelligent vehicle system under the cooperation of vehicle and road is an intelligent integrated transportation system. In the system, through dynamic analysis and technical decision-making, sensors can be used to collect and identify the environment in real time, and actively adjust the driving state of the vehicle to provide safe information services for the driver. The architecture of intelligent vehicle road collaboration system is shown in figure 3.

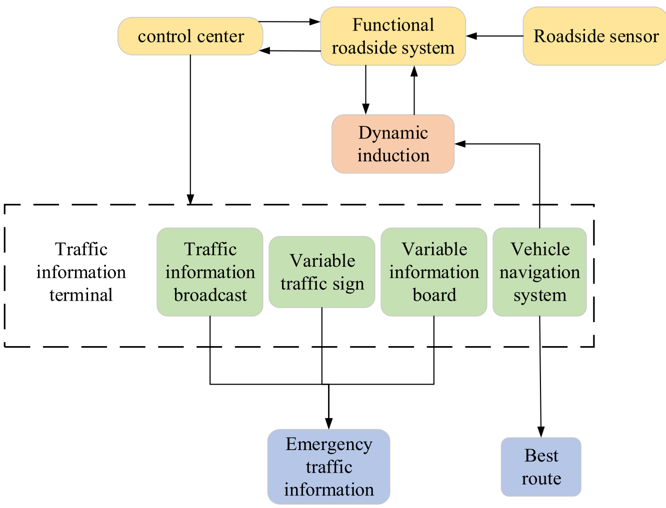

Fig. 4. Dynamic traffic guidance diagram based on vehicle road coordination.

In the process of modern urban development, with the increase of vehicles, there are more and more roads, intersections and driving vehicles, and the road conditions are more complex. For such a large-scale transportation system, vehicle safety management is a very complex work. In the traditional traffic control state, due to the lack or incompleteness of the implementation data, the dynamic traffic guidance lacks sufficient data support, while the vehicle road collaboration technology provides rich data for the dynamic traffic guidance, and uses a variety of information terminals to provide traffic guidance information for all kinds of traffic participants [27]. The dynamic traffic guidance diagram based on vehicle road coordination is shown in figure 4.

D. Safety Evaluation of Intelligent Transportation System Based on Deep Learning

Road environment is the most important factor affecting traffic safety, including vehicle density, road design speed and number of intersections. In order to analyze the system security more clearly, in this study, the system security is evaluated. The concept of deep learning comes from the research of artificial neural network. According to the definition of artificial neural network, the learning process formula of W^{21} matrix is as follows:

$$\varepsilon\frac{dn^1(t)}{dt} = -n^1(t) + ({}^{+}b^1 - n^1(t))(p + W^{21}a^2(t)) \\ -(n^1(t) + {}^{-}b^1)({}^{-}W^1a^2(t)) \quad (17)$$

In the equation, a means learning output. The output after learning is $a^1 = p \cap W_j^{21}$. The update rules for W^{21} are as follows:

$$\frac{dw_j^{21}(t)}{dt} = a_j^2(t)(-W_j^{21}(t) + a^1(t)) \quad (18)$$

The updated learning output is: $a^1 = W_j^{21}$.

In order to analyze the data propagation speed, Markov chain (figure 5) is used for analysis.

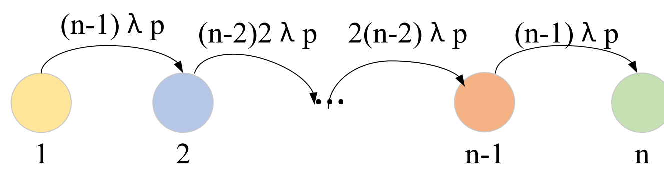

Fig. 5. Markov chain of information dissemination (n represents n different vehicles).

Where, if the vehicle receives j messages, the Markov chain is in Mj. If two moving cars follow the exponential distribution with parameter λ, the probability that the information can be successfully transmitted is p. The probability of transition from state Mj to Mj +1 is $(n-j)j\lambda\lambda$. The duration of stay in state Mi is:

$$t_i = (n-i)i\lambda\lambda p, \quad 1 \leq i \leq n-1 \quad (19)$$

The probability density function is:

$$f(t_i) = (n-i)i\lambda\lambda p^{-(n-i)i\lambda p t_i} \quad (20)$$

The time t required for information transmission to all n vehicles is:

$$T = \sum_{i=1}^{n-1} t_i = \sum_{i=1}^{n-1}(n-i)i\lambda p \quad (21)$$

If E ( ) is the expected function, T is taken into the following equation:

$$F_T(s) = E\left(e^{-s}\sum_{i=1}^{n-1} t_i\right) = \prod_{i=1}^{n-1} E\left(e^{-st_i}\right) \quad (22)$$

Using Laplace transform, the following equation can be obtained:

$$F_T(s) = \prod_{i=1}^{n-1}\frac{(n-i)i\lambda p}{(n-i)i\lambda p + s} \quad (23)$$

Finally, the expected value of T can be obtained as:

$$E(T) = \frac{2}{n\lambda\lambda}\sum_{i=1}^{n-1}\frac{1}{i} \quad (24)$$

E. Simulation Analysis

In this study, in the Matlab network simulation platform, the system is predicted and analyzed. Among them, the specific parameters of wireless communication are IEEE 802.11 MAC protocol. Two ray ground propagation model is adopted. The transmission range is 250m. In the test environment, even if the vehicle is in the range of wireless signal transmission, the signal cannot be successfully transmitted due to obstacles, signal interference, channel conflict and other factors.

In the simulation, the CPU model of the computer is CORE-i7-4720HQ-2.6GHz. The neural network is built by Tensorflow framework, which is open source of Google. It is a machine learning and deep learning programming framework based on vector flow graph. Matrix operations are performed using Numpy and Pandas open source toolkits. Numpy library is an

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE I
MODELING TOOL TABLE

	Tool version
Neural network construction	Tensorflow-gpu 1.13.1
Matrix transport	Numpy1.12.6;Pandas 0.23.0
Programing language	Python 3.2
Development platform	PyCharm

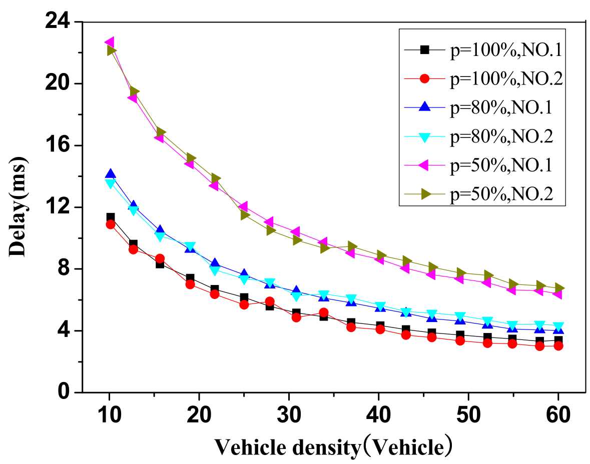

Fig. 6. Propagation delay graphs with different probability of successful transmission p when $\lambda = 0.05$.

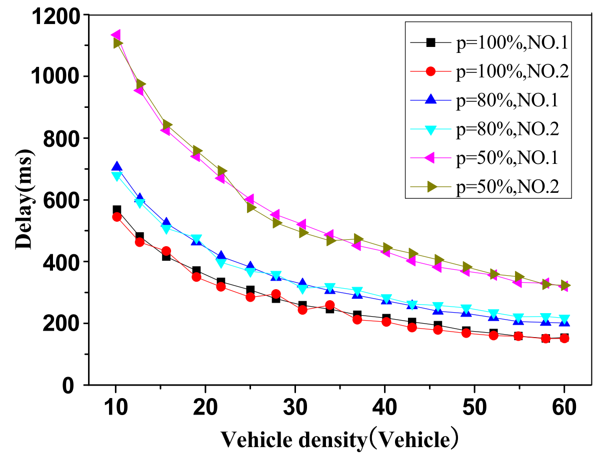

Fig. 7. Propagation delay graphs with different successful transmission probabilities p when $\lambda = 0.001$.

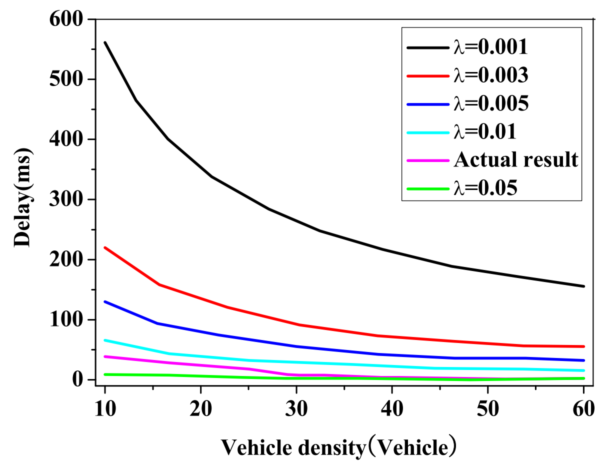

Fig. 8. Propagation delay diagram measured by experiment at p= 100%.

open-source matrix processing library. Pandas library provides good help for data cleaning and data preprocessing in data analysis. The specific modeling tools are shown in table I.

IV. RESULTS AND DISCUSSION

A. Data Transmission Performance Analysis

The data transmission performance of the intelligent transportation system is analyzed. When λ is 0.05 and 0.001, the theoretical delay of information transmission is shown in figure 6 and figure 7. When the probability of successful transmission p is 100% and 80%, the correlation between different λ values and the actual propagation delay is further analyzed.

It can be seen from figure 6 and figure 7 that when $\lambda = 0.05$ and $\lambda = 0.001$, the propagation delay decreases with the increase of the probability of successful propagation. The demonstration time is the shortest when the probability of successful propagation is 100%. Therefore, the higher the probability of successful propagation is, the shorter the propagation delay is. The magnitude of λ does not affect this correlation.

It can be seen from figure 8 that when the probability of successful propagation is 100%, different values of λ have different effects on transmission delay time. It can be found that the delay of the same λ value decreases with the increase of vehicle density. When comparing the delay between different λ values, the delay time decreases with the increase of λ value. The maximum delay time is about 550ms when $\lambda = 0.001$. When λ value is between 0.01 and 0.05, it is the same as the actual delay transmission result. Therefore, when analyzing the influence of different λ values on transmission delay time, it is found that the theoretical structure is most similar to the actual transmission result when λ value is $0.01 \sim 0.05$.

It can be seen from figure9 that when the probability of successful propagation is 80%, different values of λ have different effects on transmission delay time. It can be found that the delay of the same λ value decreases with the increase of vehicle density. When the delay between different λ values is compared, the delay time decreases with the increase of λ value. The maximum delay time is about 650ms when $\lambda = 0.001$. When $\lambda = 0.05$, the delay time approaches to 0. Moreover, it is found that when λ value is between 0.01 and 0.05, it is the same as the actual delay transmission result. Therefore, when analyzing the influence of different λ values on transmission delay time, it is found that the theoretical

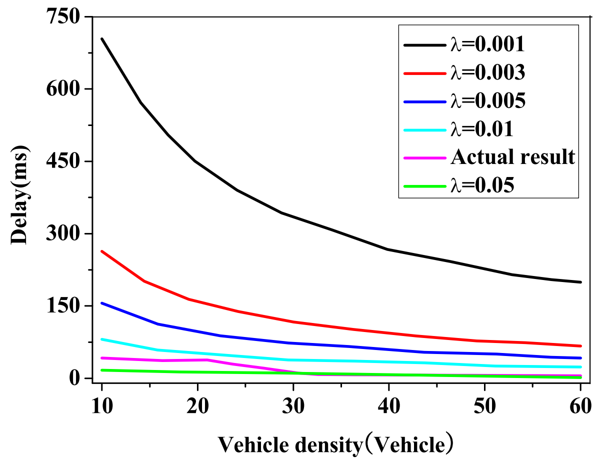

Fig. 9. Propagation delay diagram measured by experiment at p = 80%.

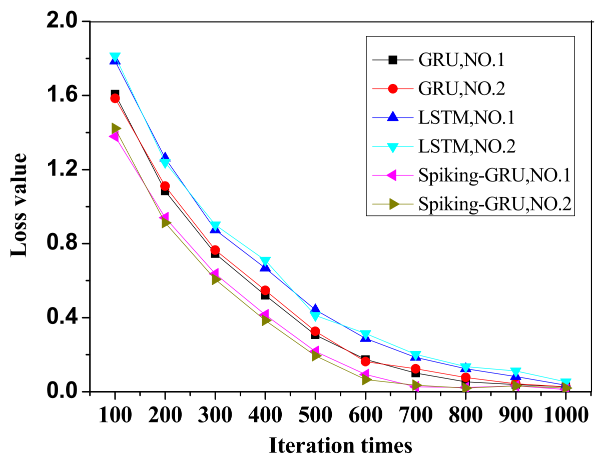

Fig. 10. The relation between the loss value of category 1 and the number of iterations.

structure is most similar to the actual transmission result when λ value is 0.01 $\sim$ 0.05.

B. Prediction Accuracy Analysis

In the accuracy prediction performance analysis of the intelligent transportation system constructed by this research institute, the original GRU, LSTM and Spiking-GRU models in this research are compared and analyzed under three types respectively (Table II). After statistical analysis, the results are shown in figure 10, figure 11 and figure 12.

From figure 10, the relationship between the loss value and the number of iterations in the case of category 1 can be seen. It can be seen from the figure that with the increase of the number of iterations, the loss values of the three models show a downward trend. When the number of iterations is 1000, the loss value tends to 0. Compared with different models, it is found that the loss value of LSTM model is the largest, that of GRU model is the second, and that of Spiking-GRU model is the smallest. Therefore, in the case of category 1, the prediction accuracy of Spiking-GRU model is significantly better than that of the other two models, with high prediction accuracy.

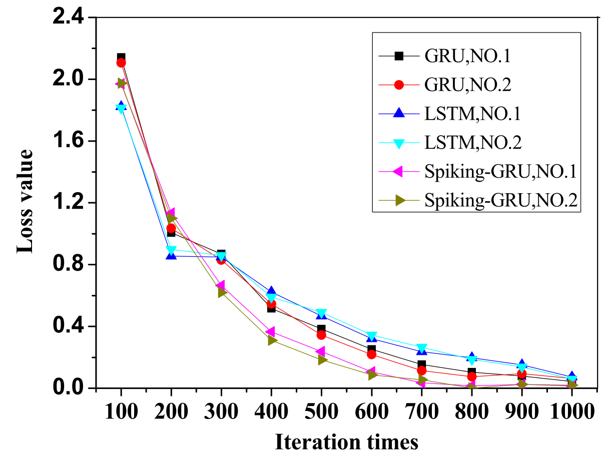

Fig. 11. The relation between the loss value of category 2 and the number of iterations.

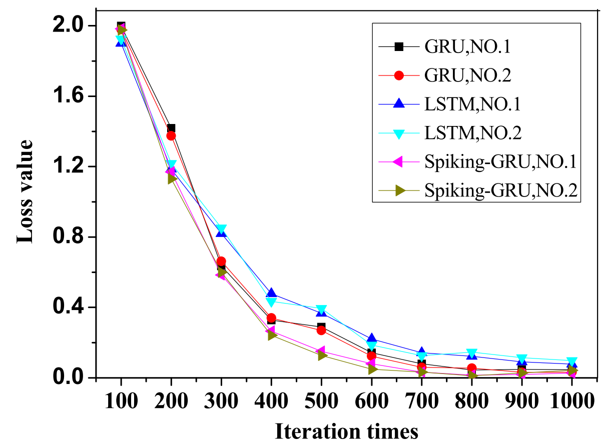

Fig. 12. The relation between the loss value of category 3 and the number of iterations.

TABLE II
AVERAGE TRAVEL TIME OF VEHICLE

	CATEGORY 1	CATEGORY 2	CATEGORY 3
AVERAGE TRAVEL TIME OF VEHICLE	411	629	924

From figure 11, the relationship between the loss value and the number of iterations in the case of category 2 can be seen. It can be seen from the figure that with the increase of the number of iterations, the loss values of the three models show a downward trend. When the number of iterations is 1000, the loss value tends to 0. Different models are compared. It is found that when the number of iterations is less than 300, the loss value of LSTM model is the smallest. However, when the number of iterations is higher than 300, the loss value of LSTM model is the largest, GRU model is the second, and Spiking-GRU model is the smallest. Therefore, in the case of category 2, the prediction performance of Spiking-GRU model is significantly better than the other two models, with high prediction accuracy.

In figure 12, the relationship between the loss value and the number of iterations in the case of category 3 can be seen.

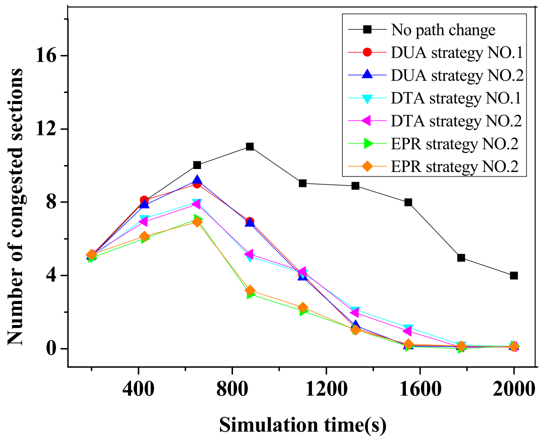

Fig. 13. System operation index (number of congested road sections) changing with time under route guidance strategy.

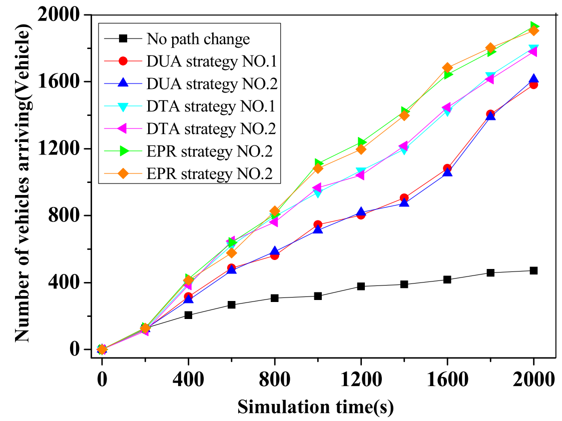

Fig. 14. System operation index (number of arriving vehicles) changing with time under route guidance strategy.

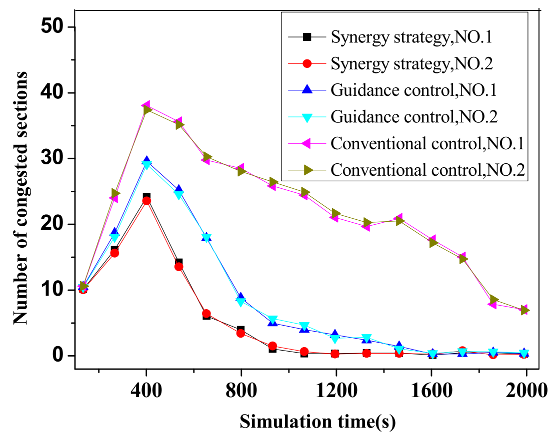

Fig. 15. System operation index chart of the number of congested road sections changing with time.

It can be seen from the figure that with the increase of the number of iterations, the loss values of the three models show a downward trend. When the number of iterations is 1000, the loss value tends to 0. When the number of iterations is less than 300, there is no significant difference among the three models. When the number of iterations is higher than 300, the loss value of LSTM model is the largest, GRU model is the second, and Spiking-GRU model is the smallest. Therefore, in the case of category 3, the prediction performance of Spiking-GRU model is significantly better than the other two models, with high prediction accuracy.

Therefore, through the comparative analysis of the prediction accuracy of different models in three categories, it is found that the Spiking-GRU model in this study has the best prediction effect.

C. Route Guidance Strategy Analysis

In the GRU performance analysis of the intelligent transportation system, the number of congested sections and the number of arriving vehicles in the simulation process are taken as evaluation indexes, which are respectively compared with the conventional traffic management strategy, DTA [28] strategy and DUA [29] strategy without GRU. The results are shown in figure 13 and figure 14.

From figure 13, it can be seen that at the beginning of simulation, the number of congested road sections increases rapidly because there is no path change. However, with the use of EPR, DTA and DUA strategies, the situation is different from that without path change over time. The number of congested road sections is significantly different from that without route change. When the operation time of the system is more than 600 s, the number of congested road sections under the three strategies is significantly reduced, and EPR route change strategy has the most obvious evacuation effect on congested road sections. Therefore, when congestion occurs, EPR strategy has a more efficient improvement effect on road conditions than other path change strategies.

From figure 14, the relationship between the number of arriving vehicles and time under the exploration route guidance strategy can be found. It can be seen that with the increase of time, the data of vehicle arrival is increasing. However, in the scheme without path change, the number of vehicle arrivals is the least, while in the EPR strategy, the number of vehicle arrivals is the most, followed by the DTA strategy, and the number of vehicle arrivals in the DUA strategy is the least, which is positively related to the road congestion in figure 13. Therefore, in the analysis of the number of road congestion and arrival vehicles, it is found that EPR strategy can effectively inhibit the spread of congestion, and evacuate the traffic congestion in time, because it uses the prediction information to avoid the possible future congestion in other places, while the DUA only uses the real-time traffic information to guide, resulting in congestion removal. DTA strategy has a relatively weak control over the congestion range, but has a strong capacity of congestion evacuation. The collaborative strategy is further compared with the individual guidance control and guidance strategy. The results of the number of road congestion and vehicle arrivals are shown in figure 15 and figure 16.

It can be seen from figure 15 and figure 16 that the synergy strategy and the guidance only control strategy are superior to the conventional traffic management control strategy, and the synergy strategy is the best for road congestion and dredging,

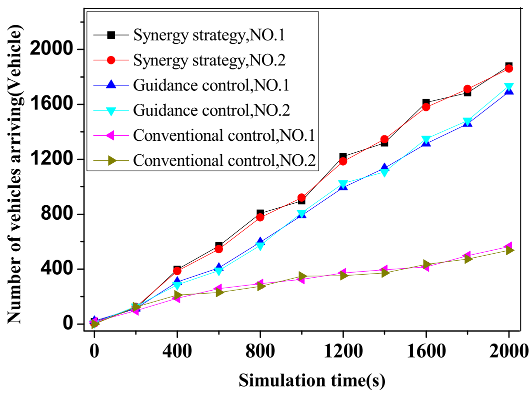

Fig. 16. System operation index chart of the number of arriving vehicles changing with time.

and has the most significant advantages in the case of a large number of arriving vehicles, especially in the case of high traffic flow. Therefore, it is speculated that in the case of road congestion, the adoption of synergy strategies can effectively inhibit the spread of congestion, and achieve the effect of timely evacuation for traffic congestion.

Through the analysis of the intelligent transportation system constructed in this study, it is found that it has good advantages in the delay of data transmission and the prediction accuracy of the system, which also leads to the avoidance of traffic safety problems in dealing with traffic congestion and vehicle route guidance strategies. Therefore, the intelligent transportation system has obvious effect on data transmission accuracy, system and traffic safety problems avoided by route guidance [30].

V. Conclusion

Nowadays, with the improvement of people's living standard, the number of vehicles in the city is increasing, and the corresponding safety problems in the transportation are also increasing. In this study, deep learning is used to solve the safety problems in the intelligent transportation system, and the algorithm is used to improve the intelligent transportation system and solve its safety problems by simulation. In the analysis of the data transmission performance of the system, it is found that when the probability of successful transmission is 100% and λ value is $0.01 \sim 0.05$, it is the closest to the actual result, and the data delay is the smallest. In the analysis of prediction accuracy, it is found that in different kinds of cases, the improved system has the best prediction performance with the increase of iterations. After further analyzing the route guidance strategy of the system, it is found that the route guidance strategy in this study can effectively inhibit the spread of congestion in the face of congested road sections, and achieve the effect of timely evacuation for traffic congestion.

In conclusion, through this study, it is found that the improved intelligent transportation system can significantly reduce the data transmission delay of the system, improve the prediction accuracy, and effectively change the path in the face of congestion so as to suppress the congestion spread, which provides experimental reference for the development of the later transportation industry. However, there are some shortcomings in this study, the experiment is still in the simulation stage, and the data collected is relatively single. Therefore, in the follow-up study, the system will be further improved to test the real-life traffic and collect more large-scale data. The data from different sources such as induction coil, monitoring video and broadcast are integrated to establish a more three-dimensional diversified prediction model, so as to provide a more reliable reference for the development of the transportation industry.

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