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Original Article

Short-Term Traffic Flow Prediction with Structure-Optimized Deep Belief Network

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Abstract

This paper proposes a structure-optimized deep belief network method for short-term traffic flow forecast, which is used to solve the problems of too simple training data in deep learning short-term traffic flow forecast and random selection of model structure construction parameters. We constructed a deep belief network short-term traffic flow forecast model that can simultaneously train three types of traffic data related to the predicted node traffic volume, enhance the spatiotemporal correlation of predictions, and overcome the shortcomings of too single training data. At the same time, we optimize the short-term traffic flow prediction model structure of the deep belief network; and use the T-PSO algorithm to optimize the hidden layer structure parameters of the prediction model. It can avoid the decrease in the practicability of the model caused by the random selection of the model structure construction parameters. The experimental results show that the method of structure-optimized deep belief network is feasible and effective, and the prediction accuracy is better than the classic deep learning prediction model.

Keywords

intelligent transportation, traffic prediction, deep learning, traffic flow, particle swarm optimization

1. Introduction

The rapid growth of traffic demand has led to a series of traffic problems becoming more prominent, traffic congestion, frequent traffic accidents, and exhaust pollution have caused many adverse effects on social development and daily life, among which traffic congestion is particularly serious. Traffic control and guidance technology can effectively alleviate traffic congestion by improving the road capacity without rebuilding the existing road conditions, so it has become an important idea to alleviate traffic congestion. Short-term traffic flow forecasting is an important prerequisite for traffic control and guidance, accurate short-term traffic flow forecasting can provide real-time and accurate future traffic flow information for the traffic control system, to formulate correct control and guidance strategies, alleviate traffic congestion, and reduce traffic accidents and reduce exhaust emissions.

Early traditional short-term traffic flow forecasting models were mostly based on statistical principles, of which the most representative is the time series model, which is derived from the continuity of traffic flow in time. This kind of method has no self-learning and self-adaptive ability, and can't capture and process the mutability and volatility of short-term traffic flow data in time, so the prediction accuracy is often not high. With the emergence of intelligent data learning and processing methods such as machine learning, the prediction accuracy and robustness of short-term traffic flow prediction methods based on machine learning have also been greatly improved, among which the representative models are the support vector regression model and the fusion model of neural network and support vector machine. These methods can self-learn from a large number of traffic flow history samples to find the inherent Patterns in the data, thus improving the prediction accuracy. However, the large amount of accurate historical traffic flow data required by these models is not readily available, and the practicability of the models is greatly limited. To achieve short-term traffic flow prediction methods, more and more deep learning-based short-term traffic flow prediction methods are applied in this field and are gradually becoming the mainstream direction of research in this field. The representative models include the long short-term memory networks model and the deep belief neural network mode. These models are more capable of self-learning data processing and can achieve accurate prediction with a small amount of representative and accurate traffic flow history data, which greatly improves the practicability of the short-term traffic flow prediction method. However, the structure of the method itself is more complex, the way and structure of data input and output, the selection of training data, and the number of layers of the deep network will affect the accuracy and real-time performance of the algorithm, which is also the key to determine whether the deep learning short-term traffic flow prediction model can be practical.

To solve the above problems, this paper proposes a short-term traffic flow prediction method based on the structure of a deep belief network (SO-DBN) with an optimized structure. Firstly, according to the type and Spatio-temporal characteristics of the prediction data, the input number and structure of the short-term traffic flow prediction model based on a deep trust network are determined, and the model framework is constructed; Secondly, determining a distribution form of an explicit layer node of an input layer of the deep belief network prediction model, a conversion relational expression of an energy function and an equivalent conversion form of data between an explicit layer and an implicit layer according to input data; Finally, considering the great influence of the model structure on the prediction accuracy, a chaotic particle swarm optimization algorithm based on T mutation is proposed to further optimize the model structure, the prediction accuracy and generalization of the algorithm are further improved by selecting the appropriate number of hidden layers.

2. Short-Term Traffic Flow Prediction Model for Deep Brief Networks

Short-term traffic flow prediction on urban roads is a scientific prediction based on the spatial and temporal evolution of traffic flow data. Traditional short-term traffic flow prediction often considers only the historical traffic flow data of the prediction node but ignores the spatial and temporal evolution of traffic flow data, and the prediction effect is often unsatisfactory. To overcome this shortcoming, this paper considers both the historical traffic flow data of the forecast node, the historical traffic flow data of the nearby important nodes, and the traffic flow data of the nearby nodes heading towards the forecast node from the historical data. To improve the prediction accuracy, the spatial and temporal evolution of the traffic flow data is fully studied and analyzed.

In order to process the above three types of data simultaneously, the deep brief network regression machine model built in this paper consists of three restricted Bozeman machine inputs with Gaussian distribution function explicit layer conversion nodes, several layers of restricted Bozeman machine intermediate layer, and support vector regression machine output layer. Each input terminal obtains an output result through the corresponding data learning and finally integrates the prediction results of the three output nodes to obtain the final predicted value. The schematic diagram of the deep brief network short-term traffic flow prediction model is shown in Figure 1.

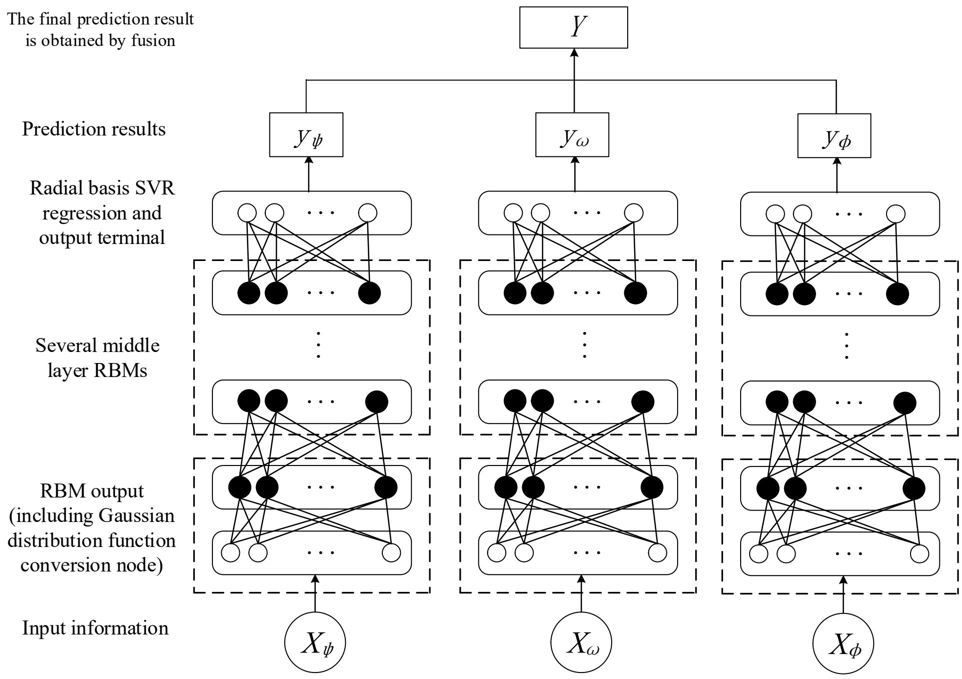


Figure 1. Schematic Diagram of Short-Term Traffic Flow Prediction Model with SO-DBN

The proposed deep brief network short-term traffic flow prediction model constructs an input layer with a Gaussian distribution function explicit layer, whose energy function is transformed by the following equation:

$$p(v,h;\theta)=\frac{\exp(-E(v,h;\theta))}{Z} \tag{1}$$

Of which, $Z=\int\sum_{h}\exp(-E(v,h;\theta))dv$

The conditional probabilities of the corresponding transitions of the explicit layer nodes in the first layer and the intermediate hidden layer nodes in the deep brief network short-term traffic flow prediction model are:

$$p(v_i=1\,|\,h;\theta)=\frac{1}{\sqrt{2\pi}\sigma_i}\exp[-\frac{(1-b_i-\sigma_i\sum_{j=1}^{J}h_j\omega_{ij})^2}{2\sigma_i^2}] \tag{2}$$

$$p(h_i=1\,|\,v;\theta)=\delta\left(\sum_{i=1}^{I}\omega_{ij}v_i+\alpha_j\right) \tag{3}$$

Among others, $\delta\left(x\right)=\frac{1}{1+e^{-x}}$

In equation (3), v is the processed fused input data, i.e. the information collected is transformed into explicit layer information, h is the equivalent implicit layer information after the transformation of the explicit layer; $E(v,h;\theta)$ is the energy function to achieve the equivalent transformation between the intermediate layer information, which is calculated as

$$E(v,h;\theta)=-\sum_{i=1}^{I}\sum_{j=1}^{J}\omega_{ij}v_ih_j-\sum_{i=1}^{I}\beta_iv_i-\sum_{j=1}^{J}\alpha_jh_j \tag{4}$$

In equation (4), $\theta=(\omega,\beta,\alpha)$ is the RBM trim parameter, I is the number of nodes in the explicit structure, J is the number of nodes in the implicit structure, β_i is the explicit node, α_j is the offset of the implicit node, and ω_{ij} is the weight parameter.

The formula for updating the RBM weights is:

$$\Delta\omega_{ij}=E_{data}(v_ih_j)-E_{model}(v_ih_j) \tag{5}$$

In equation (5), $E_{data}(v_ih_j)$ is the expectation of the training data set, $E_{model}(v_ih_j)$ is the expectation defined in the model.

After the multi-layer intermediate layer RBM data learning, its output is used as the input of the radial basis SVR regressor layer, and the prediction result of a single group of data is derived from the regressor, and the three radial basis output results y are fused according to the correlation of historical data to derive the final prediction result Y. The calculation formula is:

$$Y=\mathrm{w}_1 y_{\varphi}+w_2 y_{\omega}+w_3 y_{\phi} \qquad (6)$$

In equation(6), w_1, w_2, $w_3$are the learning parameters, which reflect the degree of influence of the historical traffic flow data of the prediction node, the historical traffic flow data of the adjacent important nodes, and the traffic flow data of the adjacent nodes heading to the prediction node from the historical data on the final prediction results.

3. Structural Optimization of a Deep Brief Network Short-term Traffic Flow Prediction Model

The number of hidden layer structures in the short-term traffic flow prediction model of deep brief networks has a large impact on the accuracy of the prediction. In order to ensure the practicality of the algorithm, a T-variant chaotic particle swarm optimization algorithm is proposed to optimize the hidden layer structure of the short-time traffic flow prediction model for the deep brief network, avoiding arbitrary construction and resulting in the reduced practicality of the model.

3.1 T-PSO Algorithm

In order to enhance the global search capability of the particle swarm algorithm, this algorithm firstly introduces a logistic mapping to generate a chaotic sequence when generating the initial particle swarm, so that the generation of particles is ordered and the global search capability is not affected by the excessive randomness of particle generation. In addition, the global search ability of the particles is improved by adding chaotic perturbation. By setting the range of chaotic perturbation and the offset position of the perturbation, the positions of the particles at the next moment calculated by the traditional particle swarm algorithm are compared with the positions of the particles after adding chaotic perturbation (Equation 7 and Equation 8 respectively), and according to the values of the objective function before and after comparing the chaotic perturbation, the appropriate positions of the particles are selected to prevent particles from falling into the local optimum region.

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad (7)$$

$$\Delta x_i^{k+1}=x_i^k+v_i^{k+1}+\Delta x \qquad (8)$$

Where is the particle, k denotes the current position, k+1 denotes the next moment position anddenotes the perturbation offset position.

Finally, to overcome the imbalance between the global exploitation capability and local fine-tuning capability of traditional particle swarm algorithms, the particle global search and local exploration capabilities are enhanced simultaneously by varying the velocity of the particles. In order to increase the tuning bandwidth of the variation function, this paper selects the T function to implement the iterative variation of particle velocity. T function is shown in equation (9):

$$f(x)=\frac{1}{(0.5,0.5n)\sqrt{n}}(1+\frac{x^2}{n})^{-\frac{n+1}{2}} \qquad (9)$$

where n is the degree of freedom parameter.

The particle position update method can be improved as follows:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{11}$$

$$n_i^{k+1} = n_i^k \exp(N(0,1) + N(0,\Delta n)) \tag{12}$$

where $T_{(n)}$ denotes the T function, $\eta_i(j)$ is the standard deviation of the T function, and w is the inertia weight value.

The calculation of the inertia weight values can be improved as follows.

$$\omega_{ij}^k = \frac{\lambda}{1+\exp[-(\beta \cdot fv_i^k)^{-1}]} + (1-\lambda)\omega_{ij}^0 \exp(-\varepsilon k^2) \tag{13}$$

In equation (13), β is the distance adjustment factor, fv is the distance feedback function, and exp(-εk2) represents the variance according to the iterative variable k.

3.2.Steps for Implementing a Deep Brief Network for Short-term Traffic Flow Prediction with Structural Optimization

The historical traffic flow data of the prediction nodes, the historical traffic flow data of the adjacent important nodes and the traffic flow of the adjacent nodes heading towards the prediction nodes in the historical data were collected as training data. The chaotic particle swarm optimization algorithm with T variance is used to optimize the hidden layer structure in the prediction model, and the average absolute error between the predicted and true values is minimized as the optimization-seeking objective function, as shown in equation (14).

$$E_{\min} = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - Y_i^*)^2}{n}} \tag{14}$$

Where Y^* , Yi are the predicted and true values respectively.

The main implementation steps of the structure-optimized deep brief network for short-term traffic flow prediction proposed in this paper are as follows.

Step l. Collect short-term traffic flow sample data, mainly including historical traffic flow data of the prediction node, historical traffic flow data of the adjacent important nodes, and traffic flow of the adjacent nodes towards the prediction node in the historical data.

Step 2. Construct a deep brief network short-time traffic flow prediction model, set up including three nodes with Gaussian distribution function explicit layer conversion restricted Bozeman machine input, restricted Bozeman machine intermediate layer and support vector regression machine output layer, initially set the number of nodes in the explicit and hidden layers, the number of hidden layers, the kernel function of the support vector regression machine and other parameter indicators.

Step 3. Select training data and test data to train the prediction model, normalize the input data according to equation l, realize the transfer of data information in the hidden layer structure according to equations 2,3 and 4, compare the differences between training data and test data, adjust the weights according to equation 5 to improve the accuracy of the training model and reduce the differences between training data and test data.

Step 4. Optimize the structure of the deep brief network short-term traffic flow prediction model by setting the values of the relevant parameters of the T-variant chaotic particle swarm optimization algorithm. The number of hidden layer structures of the prediction model is determined using Eq.14 as the objective of the optimization search. The inertia weights of the particles are calculated according to Eq. 13, and the optimal positions of the particles, i.e., the global optimal solutions, are calculated according to Eqs.10,11, and 12.

Step 5. Build the final structure-optimized deep brief network short-term traffic flow prediction model based on the optimized hidden layer structure. The trained short-term traffic flow prediction model is used to predict the actual data and verify the prediction results.

4. Experimental Results and Analysis

4.1 Sample Collection and Selection

In this experiment, three types of traffic flow data were collected from a secondary arterial road in Nanning City, the total traffic flow of two intersections adjacent to this secondary arterial road, and the traffic volume of the two intersections heading for this secondary arterial road. The topology of the experimental road network is shown in Figure 2. The interval of sample collection is 5 minutes. Specifically, the operators collect a total of 288*12 sets of data respectively for the traffic flow of the certain secondary arterial road in Nanning, the total traffic volume of the two intersections adjacent to this minor arterial road, and the traffic flow of the two intersections that heading for this secondary trunk road, corresponding to the three input ports of the model. The operator selects the three types of data collected in the first 7 days as the three input ports' training sample sets to train the proposed algorithm model structure. In addition, the test sample set to verify the algorithm's prediction performance is the data collected in the last 2 days.

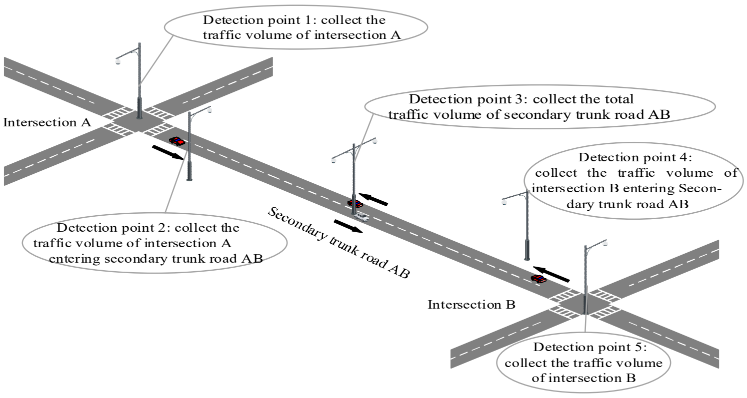


Figure 2. Topological Structure Diagram of Experimental Road Network

4.2 Analysis of the Influence of Short-Term Traffic Flow Prediction Performance of Structural Optimized-Deep Belief Nets (SO-DBN)

In order to improve the real-time performance of the prediction model, the experiment use the offline training mode to train the model. By setting up the parameters required in the algorithm, the experiment compares the prediction performance under the Structural-Optimized DBN short-term traffic flow prediction method and the Structural-Fixed DBN short-term traffic flow prediction method, to verify the validity of the SO-DBN method.

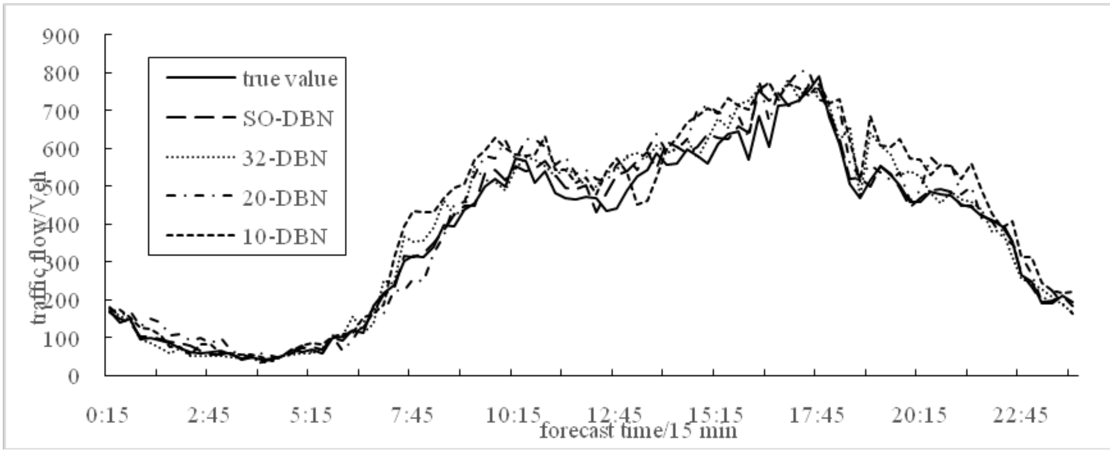
4.2.1 Setting of Related Parameters

The main parameters of the SO-DBN short-term traffic flow prediction algorithm are as follows: the value of the chaotic sequence Logistic mapping μ in the optimization algorithm is 4; the degree of freedom parameter of the T variogram has a value of 2; the value of θ in the particle position update method is 0.1; the number of iteration is 120; the number of neural nodes in each layer in the deep belief nets is 80, and the number of hidden layers is dynamically selected by the optimization algorithm according to the value of the objective function.

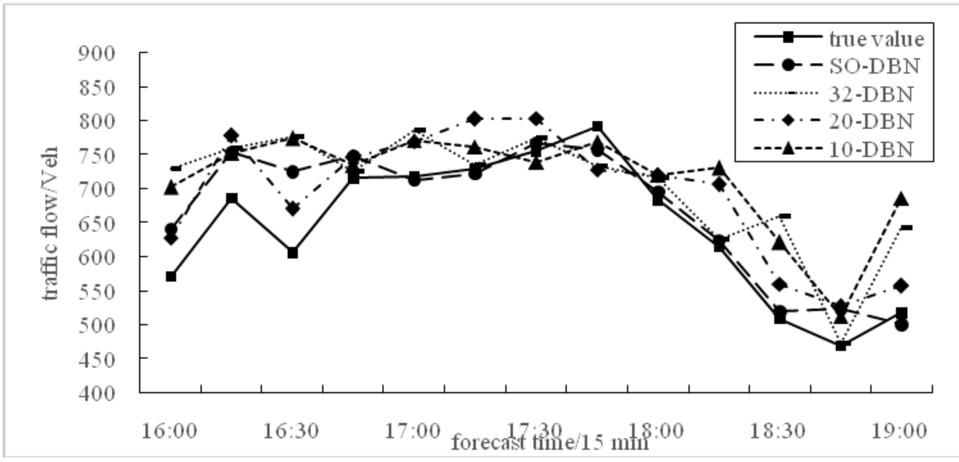
The number of neural nodes in each layer is 80 for the structural fixed deep belief nets short-term traffic flow prediction method, and the number of hidden layers is fixed values, which are 10, 20, and 32 respectively.

4.2.2 Algorithm Performance Comparison

Input 576 sets of test data into the trained SO-DBN model to predict the 15-minute traffic flow in each time period on November 29. In addition, The 10 layer hidden layer deep trust network short-term traffic flow prediction model (10-DBN), 20 layers hidden layer deep trust network short-term traffic flow prediction model (20-DBN), and 32 layers hidden layer deep trust network short-term traffic flow prediction model (32-DBN) are used to predict the original experimental set data, and the prediction results are compared with SO-DBN model, The results are shown in Figure 3, in which Figure 3 (a) is the comparison diagram of 24-hour prediction results of three methods, and Figure 3 (b) is the comparison diagram of prediction results in late peak hours.



(**a**) Comparison chart of 24 hour forecast results



(**b**) Comparison chart of evening peak prediction results from 16:00 to 19:00

Figure 3. Comparison of Prediction Results between SO-DBN and Fixed Deep Belief Network

4.2.3 Analysis of Prediction Results

In this paper, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R-square () are used as evaluation indexes. The prediction results of SO-DBN model, 10-DBN, 20-DBN and 32-DBN model are shown in Table 1.By comparing the three indicators, it can be seen that the choice of the number of hidden layer structure layers has a direct impact on the prediction accuracy of the algorithm. The prediction result of SO-DBN model proposed in this paper is better than the other three short-term traffic flow prediction methods of deep trust network with fixed structure, followed by 20-DBN model, 10-DBN model is the worst and 32-DBN model is only better than the 10-DBN model.

Table 1. Evaluation of Prediction Results

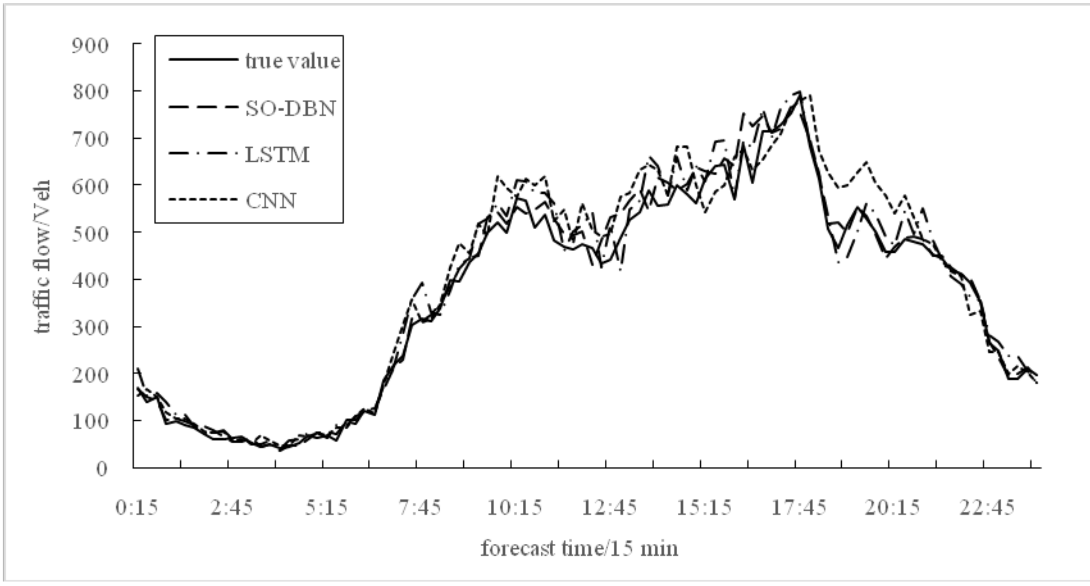
evaluating indicator	10-DBN	20-DBN	32-DBN	SO-DBN
MAE	55.3750	43.0312	45.5729	19.0625
RMSE	43.4375	29.9271	33.0937	10.9167
R2	0.9614	0.9713	0.9694	0.9872
MRE%	15.9701	15.0259	15.3363	6.2738

4.3 Comparison of Prediction Performance between Deep Trust Network Model for Structural Optimization and Classical Algorithm

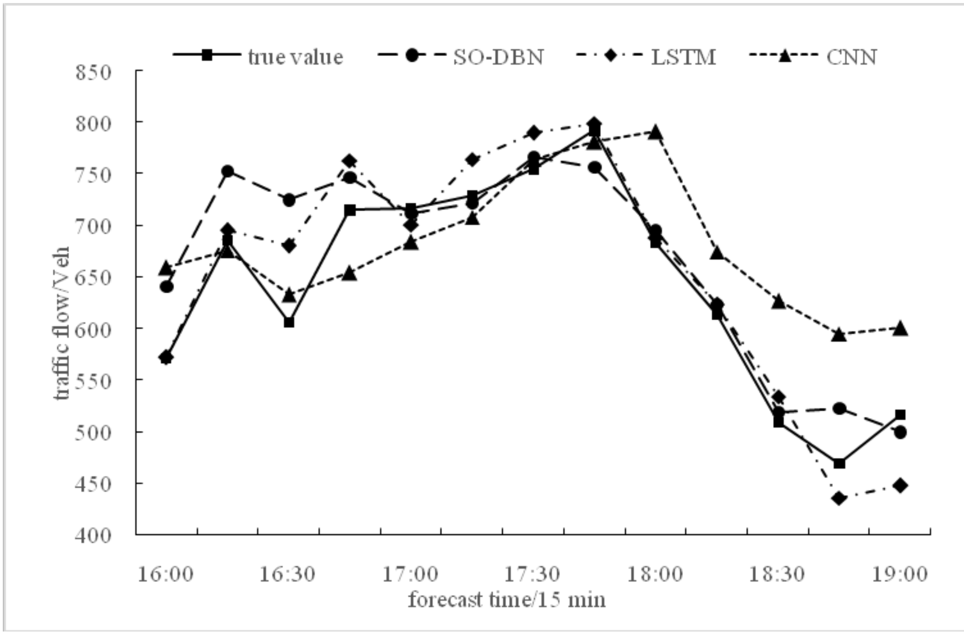
The structure optimized deep trust network short-term traffic flow prediction method (SO-DBN) proposed in this paper is compared with the prediction effects of the classical Long Short-term Memory Networks (LSTM) short-term traffic flow prediction method and deep Convolutional Neural Networks (CNN) short-term traffic flow prediction method. Finally, the results are obtained.

4.3.1 Algorithm Performance Comparison

The 576 sets of test data in the test set are fed into the trained SO-DBN model to predict traffic flow for each time period of 15 minutes on November 29. Meanwhile, the LSTM model and CNN model are used to predict the original experimental set data, and the prediction results are compared with the SO-DBN model, as shown in Figure 4.



(**a**) Comparison Chart of 24-Hour Forecast Results



(**b**) Comparison Chart of Prediction Results of Evening Peak between 16:00 and 19:00

Figure 4. Comparison of Prediction Results between SO-DBN and Classic deep Learning Models

4.3.2 Analysis of the Experimental Results

In this study, the performance of the model was evaluated by Root-Mean-Square Error (RMSE), Mean Absolute Error (MAE) and R-Square (R2). The evaluation results are shown in Table 2, from which we can see that SO-DBN method has the highest accuracy and perform better than the other two classical deep learning short-time traffic flow prediction methods.

Table 2. Evaluation of Prediction Results

evaluation index	LSTM	CNN	SO-DBN
MAE	28.6042	39.3750	19.0625
RMSE	19.1250	27.9375	10.9167
R2	0.9813	0.9648	0.9872
MRE%	9.8643	11.4889	6.2738

4.4 Computational Efficiency Analysis of Deep Belief Network Models with Structural Optimization

The computational efficiency of the short-time traffic flow prediction model is the key to the practicality of the algorithm. In order to verify the computational efficiency of the algorithm, this paper evaluates it with the algorithm operation time as the evaluation index; and compares it with the classical LSTM [9] and CNN models [10]. This experiment takes an offline training model after online prediction data for short-time traffic flow prediction. This experiment takes an offline training model and then predicts the data online for short-term traffic flow prediction. The experimental platform used is: a 2.10 GHz Intel E5 CPU, 8GMB memory, and python programming language. The computational efficiency of the algorithm is shown in Table 3. As can be seen from Table 3, although the algorithm is not optimal in terms of real-time performance, the gap between the algorithm with optimal real-time performance is not large, and computational efficiency is still high enough to meet practical use requirements.

Table 3. The Computational Efficiency of Different Models

Algorithm name	Time-consuming algorithm/S
SO-DBN	23
LSTM	20
CNN	61

5. Conclusions

This paper proposes a structure-optimized deep belief network method for short-time traffic flow prediction. The method enhances the Spatio-temporal correlation of prediction, by simultaneously training three types of traffic flow data associated with the predicted nodes. In order to further improve the accuracy of the prediction model, this paper proposes a T-variant chaotic particle swarm optimization algorithm. And then optimize the structure of the short-time traffic flow prediction model of the deep belief network, and dynamically select the appropriate parameters of the hidden layer structure of the prediction model.

Using actual traffic data for method validation, the experimental results show that the structure-optimized deep belief network short-time traffic flow prediction method proposed in this paper has better prediction accuracy than LSTM and CNN models, better prediction effect, and real-time performance can also meet the practical needs.

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