Investigation on the Traffic Flow Based on Wireless Sensor Network Technologies Combined with FA-BPNN Models

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Abstract

In this paper, both the four kinds BPNN models can predict the trends of Lozi and Tent chaotic time series. In terms of the predicted effect, the traditional BPNN model performs the worst effect because its predicted effect is far from the real data, while the improved GA-BPNN model and PSO-BPNN model reflect basically the real data. Among these, the proposed FA-BPNN model is the best, which predicted results are basically coincident with the real data. In the respect of the running time, the traditional BPNN model has the longest running time, GA-BPNN model and PSO-BPNN model followed, while the proposed FA-BPNN model has the shortest running time. Therefore, the proposed FA-BPNN model in this paper is feasible and effective. Then, the proposed FA-BPNN model is used to improve the data fusion in WSN technologies. Finally, the improved WSN technologies are used to collect the actual traffic flow, but the cost is always very high. Therefore, the proposed FA-BPNN model is used to predict the actual traffic flow. Compared with the other three kinds of BPNN models, the proposed FA-BPNN model has the best effect and the shortest running time in the traffic flow prediction.

Keywords: Chaotic time series, FA-BPNN model, WSN technologies, Traffic flow

1 Introduction

In recent years, with the development and maturity of technologies such as micro-motor system, embedded computation, wireless communication with low power, micro sensor and integrated circuits, a lot of micro sensors with low power, small size, short-distance communication and low cost could be organized into a wireless sensor network through wireless communication [1-5]. A lot of sensor nodes integrate multiple functions such as information collection, data processing and wireless communication. They are distributed in a bad monitoring environment to constitute a wireless sensor network. Through cooperation, they complete tasks such as sensing of monitored objects in a monitoring region, information collection and data processing. In recent years, wireless sensor networks have presented outstanding advantages because of the application flexibility, low cost, convenient layout and other features [6-10]. A lot of organizations have applied wireless sensor networks to study the field and achieved some achievements.

Han and Han [11] proposed a novel Kalman information collection method with WSN based on principles of metal electromagnetic. Initial vehicle information data is obtained according to principles of metal electromagnetic; zero mean processing is conducted on the initial information data; and a time sequence model of information can be determined. Aiming at the specific traffic puzzle of slope turning, Xu et al. [12] studied and achieved a slope turning reminding system based on wireless sensor network (WSN). Wang et al. [13] introduced a traffic detection system based on wireless sensor networks, where the moments when a movable node arrived at beacon nodes were determined according to size of RSSI values received by the two beacon code nodes with known distances were arranged on the roadside. Aiming at problems such as energy consumption imbalance and high energy consumption of cluster head in the routing algorithm in WSN nodes, Li et al. [14] proposed a path optimization algorithm with introduction of WSN into traffic based on GA and LEACH. As WSN is an important tool to collect real-time traffic information, the node energy is limited and a clustering routing algorithm with high energy efficiency must be designed to extend the network cycle, Cao et al. [15] designed an application model of WSN in intelligent traffic. Aiming at the problem of control of traffic signals at multiple intersections, Tian and Du [16] proposed a two-stage organizational structure based on WSN and established a control platform of traffic signals. According to traffic information collected by sensor nodes, wireless intelligent control of traffic signals was achieved

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through fuzzy control. Tacconi et al. [17] proposed system architecture for enabling mobile nodes to query a largely deployed wireless sensor network in an intelligent transportation system scenario. Traffic information acquisition is often implemented by video cameras or inductive loops, which is expensive or inconvenient from installation and maintenance perspectives. Therefore, Wang et al. [18] designed and implemented a pervasive traffic information acquisition system based on wireless sensor networks called EasiTia.

However, those reported researches mainly focus on monitoring of traffic conditions and rarely report application of WSN technologies in traffic flow collection.

Aiming at advantages of WSN in intelligent traffic field, the paper established a WSN traffic flow collection and transmission system. The system is composed of one node, several traffic information monitoring nodes and several communication relay nodes. With a highway as the tested object, collection and transmission tests were conducted on traffic flows. An advanced BP neural network model was used to predict actual traffic flows, so that a rapid and effective traffic flow prediction model could be found. The paper rationally combines WSN with BP neural network technologies in intelligent traffic field.

2 The FA-BPNN Model and Verification

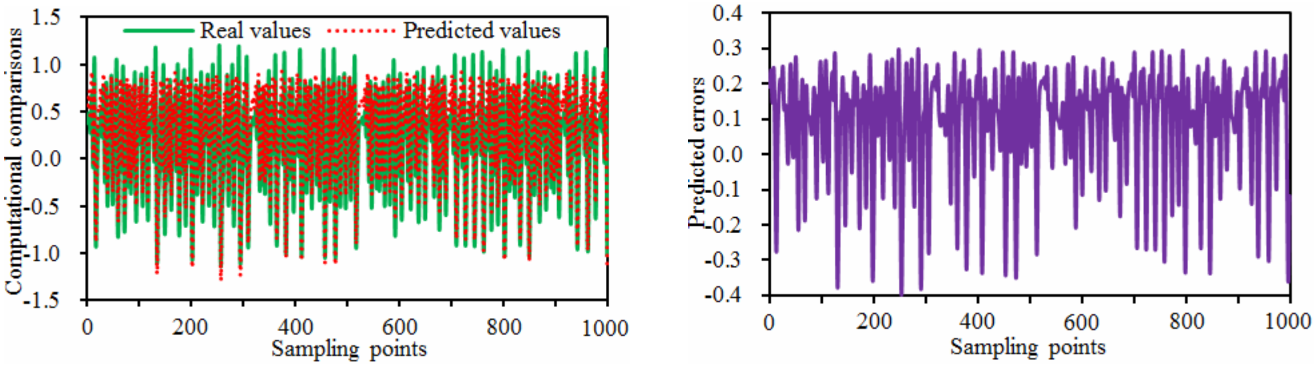
2.1 The FA-BPNN Model

The paper needs to use a BP neural network to predict actual traffic flows. Therefore, it should be discussed and selected in details. BP neural network is a multi-layer feed-forward neural network which is the most widely used neural network model among a number of artificial neural network models [19-21]. Its structure includes input layer, hidden layer and output layer. Each layer includes a lot of nerve cells with parallel computation. Two adjacent layers in the network are totally interconnected. Nodes on the same layer are not connected. Connection weights and thresholds in the network could e adjusted. Therefore, the network can conduct parallel computation of a lot of data and solve complicated nonlinear problems, presenting strong computation capacity, self-adaptability and learning ability. Meanwhile, the BP neural network stores information by states of each nerve cell as well as their connection styles. One piece of information can be stored at difference places of the network. It is distributed everywhere in the network according to contents, namely each place on the network stores a part of contents of multiple pieces of information. The complete network stores information at different places of the network after multiple pieces of information were processed. Hence, the BP neural network is capable of distributed storage. In addition, because of the distributed storage style, the BP neural network has very strong fault tolerance and robustness. In this way, even if a part of information is damaged or lost, the network recovers the originally complete information and the system can still continue the normal running. In view of its advantages and features of its application, in the age of rapid development of information technologies and economy, the application prospect of the BP neural network will be wider. However, the BP neural network also has some inevitable defects such as difficult selection network structure, local extremes, poor generalization ability, etc. Especially with the increase of training samples, the convergence of BP algorithm would be slower and the network performance would be poorer. If good initial weight and threshold are not selected for the BP neural network, its convergence would be difficult and prediction effects would be very poor.

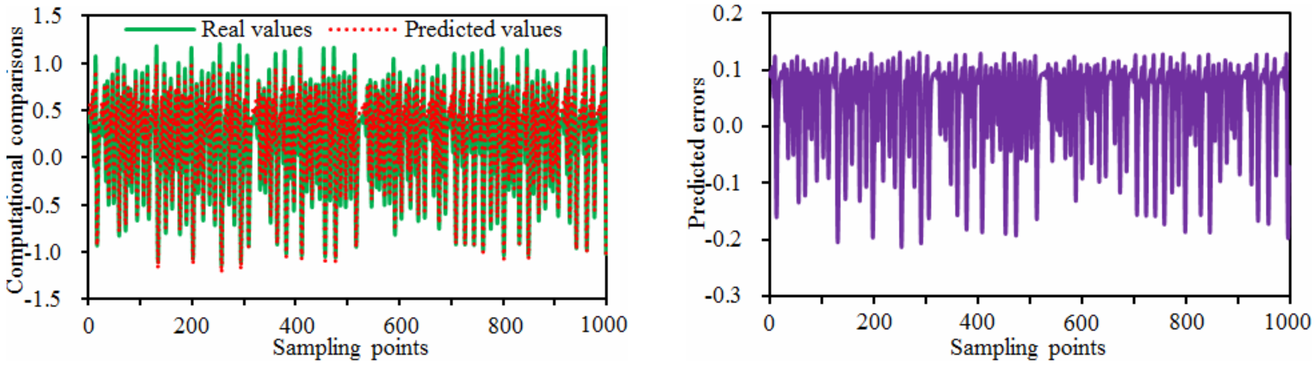
Firefly algorithm has presented a good application prospect in many fields [22-24]. It is a novel bionic optimization algorithm which simulates courtship or foraging of fireflies in the nature. Compared with other intelligent optimization algorithms, the firefly algorithm is advantaged in the simple concepts, clear processes, fewer parameters and easy implementation. No complete math basis could support the firefly algorithm at present. But a lot of researches indicate that the firefly algorithm has very good global search ability, high convergence efficiency and optimal convergence results. The local extremes could be avoided.

2.2 Verification of the FA-BPNN Model

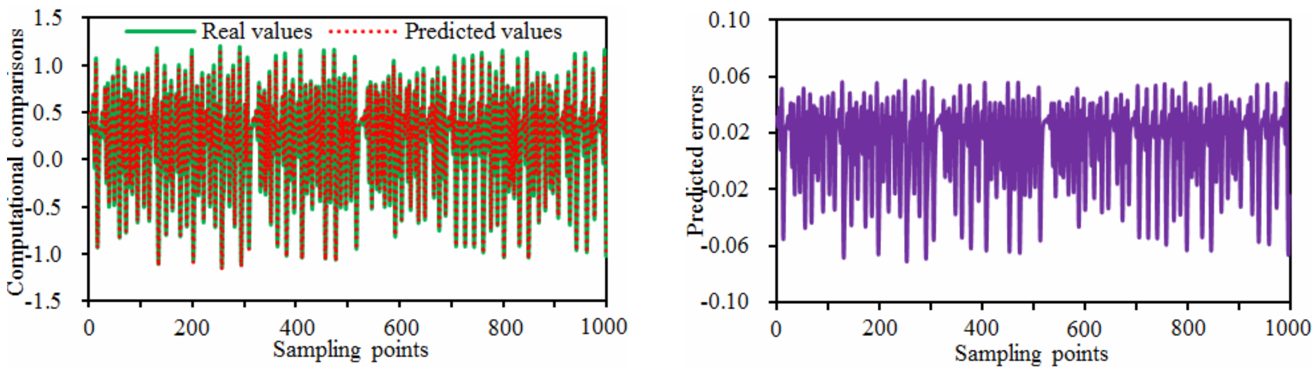
Hence, the paper proposed the FA-BPNN algorithm, namely the FA algorithm is used to improve convergence speed and global search ability of the BP neural network. In order to verify reliability and advantages of the proposed FA-BPNN algorithm, it was used to predict two kinds of chaotic time series. Obtained results were compared with predicted results of BPNN, GA-BPNN [25] and PSO-BPNN [26]. The four kinds of BP neural network models adopted the same topological structure including 1 input layer, 1 hidden layer and 1 output layer. The node amount of the hidden and input will be ensured by the analyzed problem. In the experiment, 2000 sampling points were set; the first 1000 sampling points were taken as the training data and used to predict those BP neural network models; the last 1000 sampling points were taken as the predicted data. Finally, predicted results for two kinds of chaotic time series using different BP neural network models are shown in Figure 1 and Figure 2.



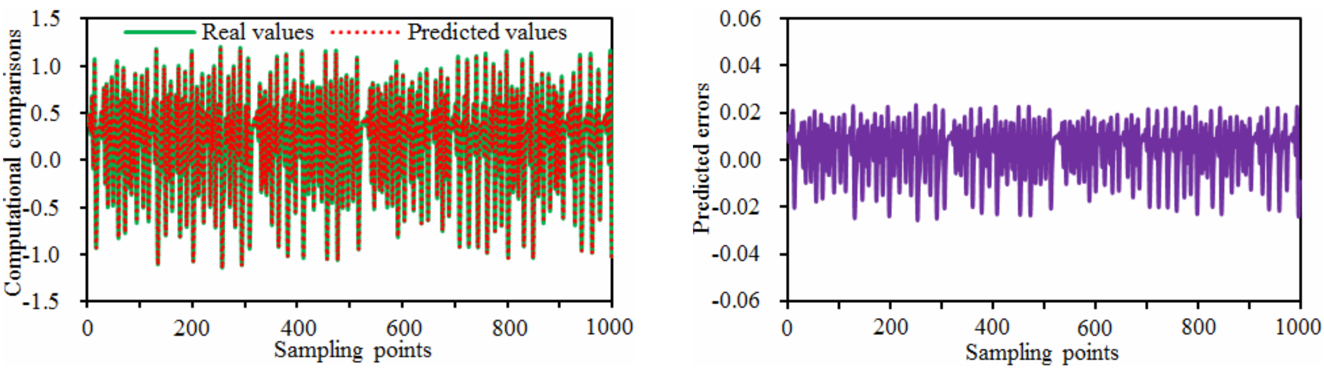
(a) BPNN model



(b) GA-BPNN model

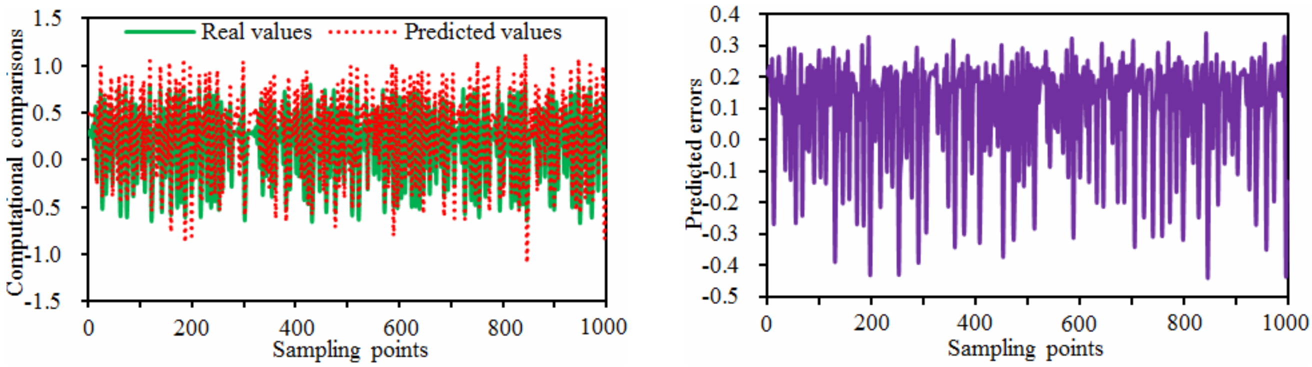


(c) PSO-BPNN model

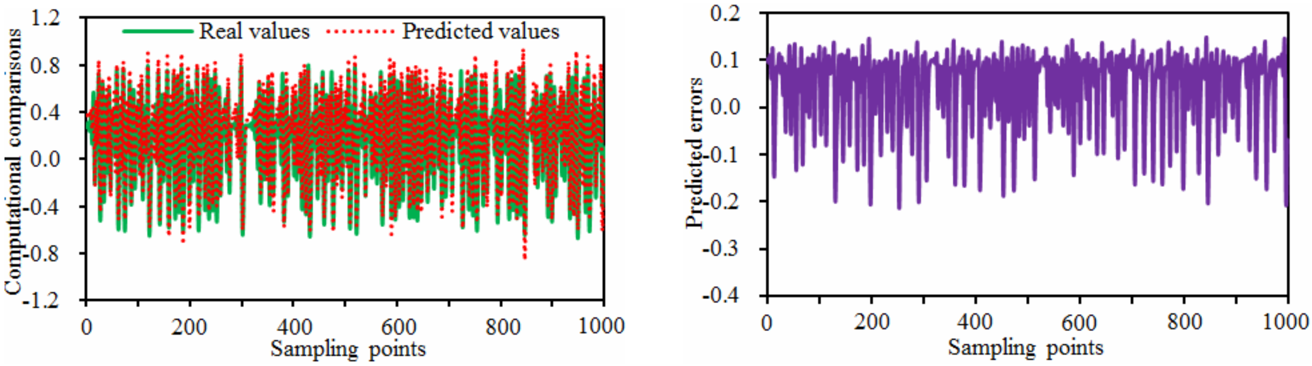


(d) FA-BPNN model

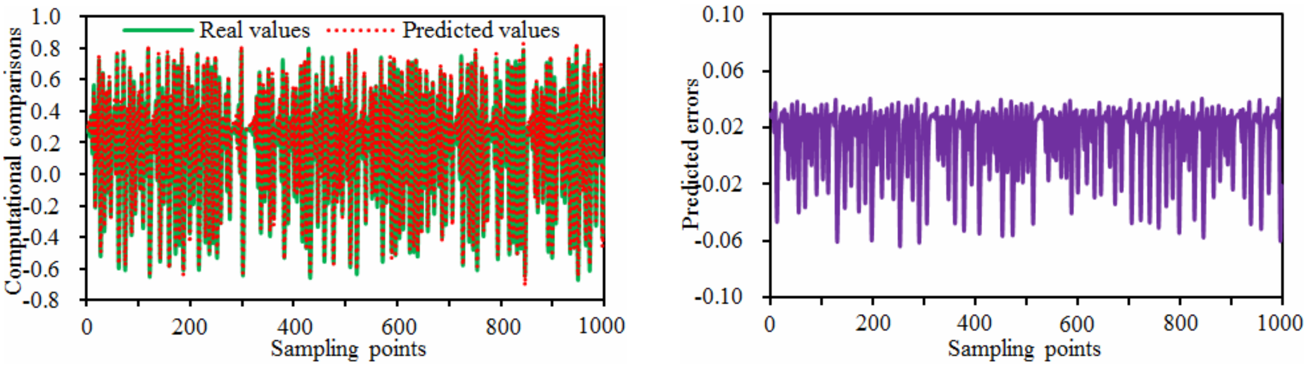
Figure 1. Lozi chaotic time series model



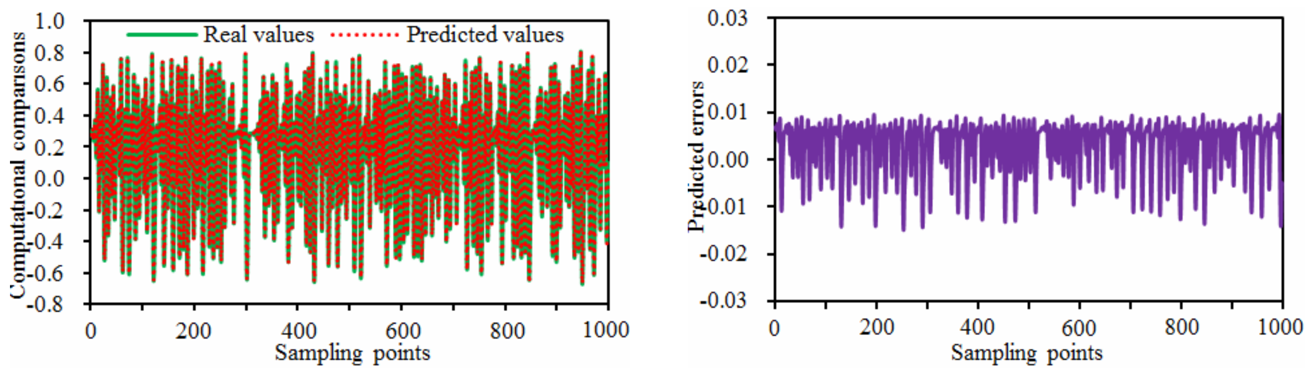
(a) BPNN model



(b) GA-BPNN model



(c) PSO-BPNN model



(d) FA-BPNN model

Figure 2. Tent chaotic time series model

Figure 1 shows predicted results obtained through using 4 kinds of neural networks aiming at Lozi chaotic time series. It is shown in this figure that predicted results obtained by using the traditional BP neural network model had the largest error. The neural network model has defects and could easily fall into local extremes during iterations. Predicted results obtained by using the FA-BPNN model proposed in the paper had the minimum error, indicating that the model is obviously better than other BPNN models. In order to further compare four kinds of BPNN models, their Mean Absolute Error (MAE) and Proportional Error (PERR) were computed, as shown in Table 1. It is shown in this table that MAE (Mean Absolute Error) and PERR (Proportional Error) of the traditional BPNN model were 0.0571 and 0.2511, and the predicted process lasted for 18s. Predicted errors and running time of the improved GA-BPNN and PSO-BPNN models were smaller than those of the traditional BPNN model. However, their predicted errors and running time were slightly higher than those of the FA-BPNN model proposed in the paper. Hence, the FA-BPNN model proposed in the paper has high efficiency and accuracy. Compared with other intelligent optimization algorithms, the firefly algorithm is advantaged in the simple concepts, clear processes, fewer parameters and easy implementation. As a result, the firefly algorithm is applied to the BPNN model, which will improve the performance of the BPNN model seriously.

Table 1. Predicted errors and running time of Lozi model system

Predicted model	MAE	PERR	running time
BPNN	0.0571	0.2511	18s
GA-BPNN	0.0436	0.2321	15s
PSO-BPNN	0.0182	0.1217	11s
FA-BPNN	0.0075	0.0699	7s

In order to further verify the FA-BPNN model proposed in the paper, four kinds of models including BPNN, GA-BPNN, PSO-BPNN and FA-BPNN were used to predict the Tent chaotic time series again. The network topology structure was kept consistent with that of Lozi chaotic time series. Predicted results and errors of four kinds of BPNN models are shown in Figure 2. It is shown in this figure that predicted error using the traditional BP neural network model was still the maximum. The neural network model has defects and could easily fall into local extremes during iterations. Using the FA-BPNN model proposed in the paper had the minimum prediction error, indicating that the model is obviously better than other BPNN models. In order to further compare four kinds of BPNN models, MAE and PERR were computed, as shown in Table 2. It is shown in the table that, MAE and PERR of the traditional BPNN model were 0.0193 and 0.2871, and the predicted process lased for 17s. Predicted errors and running time of the improved GA-BPNN model and PSO-BPNN model were smaller than those of the traditional BPNN model. However, their predicted errors and running time were more than those of the FA-BPNN model proposed in the paper. Hence, experimental results once again indicate that the FA-BPNN model proposed in the paper has high efficiency and accuracy.

Table 2. Predicted errors and running time of Tent model system

Predicted model	MAE	PERR	running time
BPNN	0.0193	0.2871	17s
GA-BPNN	0.0154	0.2426	13s
PSO-BPNN	0.0082	0.1766	10s
FA-BPNN	0.0057	0.1044	8s

3 Traffic Flow Monitoring and Prediction Based on WSN and FA-BPNN Technologies

Wireless sensor networks (WSN) are widely applied in fields such as environmental monitoring, industries and oceans [27-30]. Monitoring scopes of sensor nodes overlay each other, leading to data redundancy. The data fusion technology of WSN could effectively remove the redundant data and reduce communication cost, so that energy consumption of the network could be optimized and life cycle of the network could be increased. Therefore, it is important to use the data fusion technology in WSN.

BPNN model is applied in WSN data fusion, which is called as BPDF (BPNN Data Fusion) algorithm. It is mainly based on the LEACH clustering routing protocol. At first, the complete WSN shall be treated by cluster, and each sensor node sends the monitored data to cluster head nodes. Then, data fusion was conducted to cluster head nodes and member nodes in relevant clusters by the BPNN model. At the beginning, the fusion computation would carry out initial processing of data monitored by each sensor node according to the neural network function of input layer. The processed results are sent to other cluster head nodes. Then, cluster head nodes will conduct subsequent processing according to the nerve cell function in the hidden layer and the output layer. Finally, the data obtained after processing will be sent by cluster head nodes to a base station. Model structure of BPDF algorithm is shown in Figure 3.

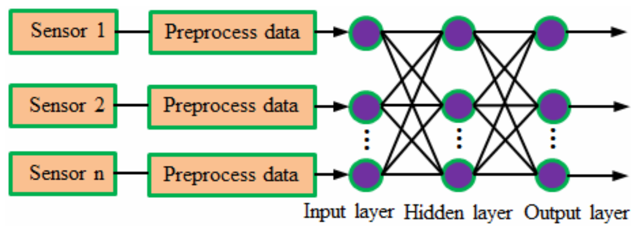


Figure 3. Model structure of BPDF algorithm

The three-layer BPNN model is selected as it is corresponding to one cluster in WSN. Hence, member nodes in the cluster could be deemed as nodes on the network input layer of BPDF, and the hidden layer and output layer are on the cluster head nodes. Analyzed results in Section 2 indicate that the FA-BPNN model proposed in the paper has obvious advantages. Hence, the paper considers applying the FA-BPNN model in WSN data fusion. In performance assessment of WSN, network nodes could effectively reflect network efficiency of the complete WSN. Hence, in view of network node energy, the FA-BPNN model proposed in the paper was compared with the traditional BPNDA and SOFMDA algorithms, as shown in Figure 4. It is shown in these figures that, the network node energy under FA-BPNN was 28J at the moment of 300s, while values of other two algorithms were 23J and 20J. The result indicates that FA-BPNN effectively balances energy consumption of WSN nodes, and extends life cycle of the complete network. Energy consumed in wireless sensors mainly refers to energy consumption during data transmission between nodes, so energy balance in FA-BPNN is also attributed to that the BPNN model optimized by firefly algorithm could effectively reduce the data transmission. Finally, energy consumption of sensor nodes could be reduced.

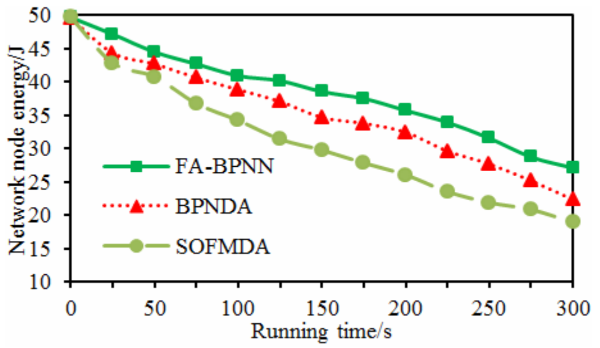


Figure 4. Node energy in wireless sensor networks

Aiming at defects in traditional traffic flow collection proposals, the paper discusses a road traffic flow collection method based on WSN and relevant technologies, as shown in Figure 5. There are 16 sensor nodes in this model. Basic ideas include: Sensor nodes are buried on a dual-way road; these buried sensor nodes are connected with the Sink node which takes charge of network starting and establishment; then, the Sink node is connected to a base station node; the base station node will transmit data to a real-time communication server. When the system is started, the node will select a communication channel and a network and then start the complete network. After the network is started, it will control working states of sensor nodes in the network, including access control of nodes, node status control, status monitoring, dynamic analysis of WSN, sending of control instructions of WSN at right time, and implementation of collection data. On one side, the nodes are connected to a traffic signal controller at the intersection and send the collected traffic information to the traffic signal controller. The traffic signal controller analyzes and processes the collected data and commands traffic signals according to the real-time data information. On the other side, the nodes send the data collected by collection sub-systems to a remote processing center. The remote processing center is one or more than one computers or embedded equipment capable of data processing and analysis. They are mainly used to conduct analysis and processing according to data sent by each subsystem of traffic information and transmission; release road condition information and make decisions.

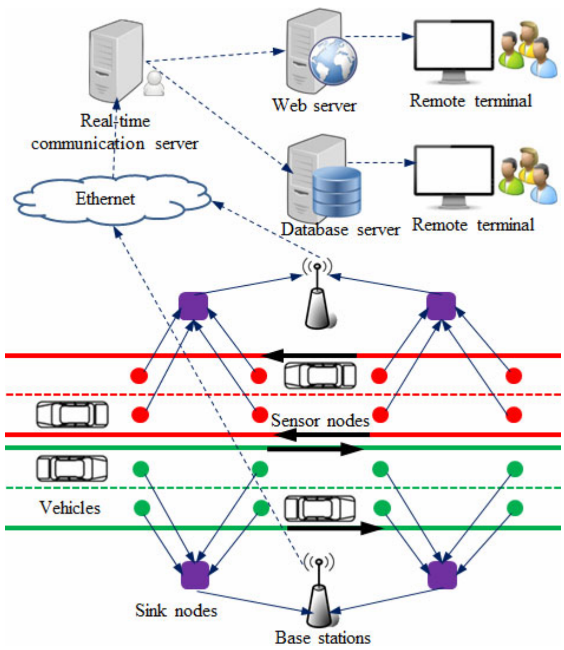


Figure 5. Traffic flow monitoring using WSN technologies

The intelligent traffic monitoring system in Figure 5 monitored traffic flows of the dual-way road in real time. In this paper, we only extracted traffic flows of the single-way road for analysis, as shown in Figure 6. Observation lasted for 5000h. 20 min was taken as the time interval. Traffic flows in each time interval were recorded. Traffic flow value in each time interval was computed by Formula (1).

$$V=60N/T \tag{1}$$

Where: V is traffic flow in a time interval. T is the selected time interval. N is the quantity of vehicles within the time interval.

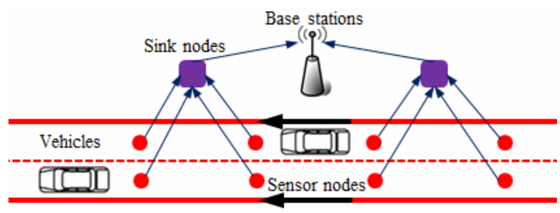
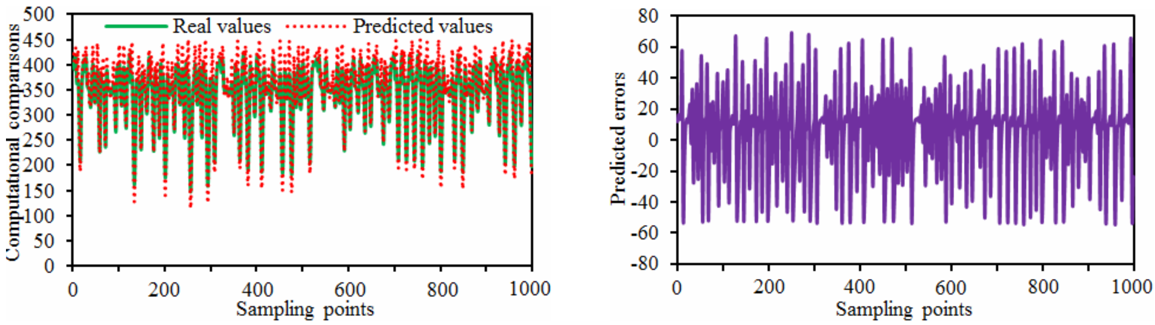
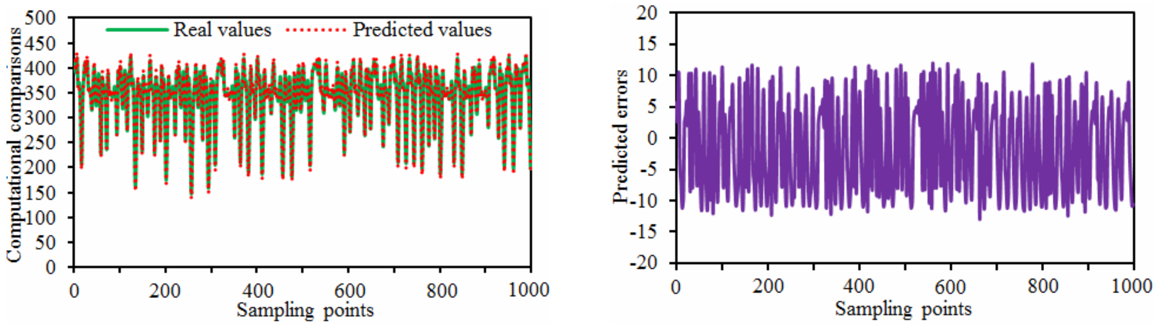


Figure 6. Traffic flow collection of single-way road

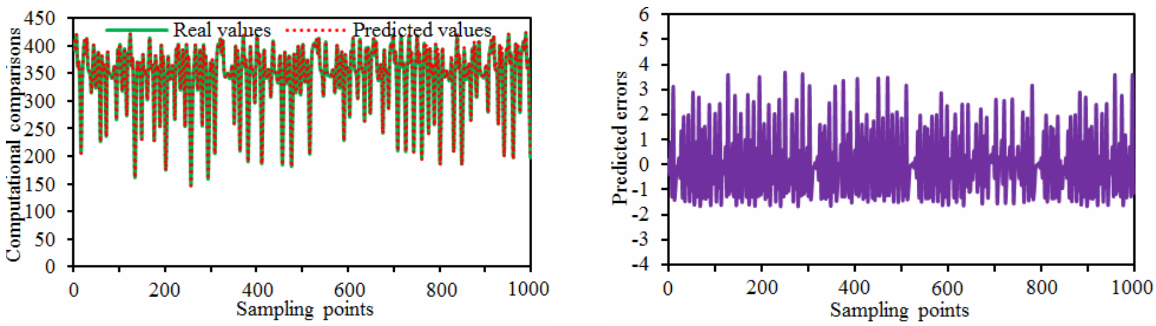
Actual traffic flows on the road could be obtained by WSN, but the cost is always very high. The analyzed results indicate that the FA-BPNN model proposed in the paper has obvious advantages. Therefore, the FA-BPNN model was used to predict the actual traffic flow. Obtained results were compared with those of other three kinds of BPNN models, as shown in Figure 7. It is shown in this figure that the BPNN models had different prediction error magnitudes. The FA-BPNN model proposed in the paper had the minimum error. The traditional BPNN model had the maximum prediction error. In order to further compare these four kinds of models, their MAE and PERR were computed, as shown in Table 3. It is shown in the table that MAE and PERR of the traditional BPNN model were 0.0472 and 0.5761, and the predicted process lasted for 21s. Predicted errors and running time of the improved GA-BPNN and PSO-BPNN models were smaller than those of the traditional BPNN model. However, compared with the FA-BPNN model proposed in the paper, their prediction errors and running time were larger. Therefore, the FA-BPNN model proposed in the paper has high efficiency and accuracy in traffic flow prediction.



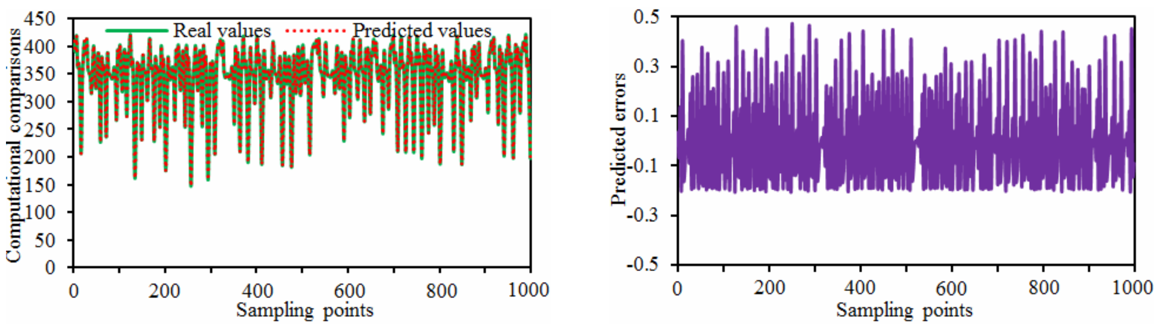
(a) BPNN model



(b) GA-BPNN model



(c) PSO-BPNN model



(d) FA-BPNN model

Figure 7. Traffic flow prediction results of four BPNN models

Table 3. Predicted errors and running time of the traffic flow

Predicted model	MAE	PERR	running time
BPNN	0.0472	0.5761	21s
GA-BPNN	0.0366	0.4223	16s
PSO-BPNN	0.0235	0.3115	13s
FA-BPNN	0.0098	0.1933	9s

4 Conclusions

From Figure 1, Figure 2 and Table 1, Table 2, we can easily find that both the four kinds BPNN models can predict the trends of Lozi and Tent chaotic time series. In terms of the predicted effect, the traditional BPNN model performs the worst among the four kinds of BPNN models because its predicted effect is far from the real data, while the improved GA-BPNN model and PSO-BPNN model reflect basically the real data. Among these, the proposed FA-BPNN model is the best, which predicted results are basically coincident with the real data. In the respect of the running time, the traditional BPNN model has the longest running time, GA-BPNN model and PSO-BPNN model followed, while the proposed FA-BPNN model has the shortest running time. Therefore, the proposed FA-BPNN model in this paper is feasible and effective. Then, the proposed FA-BPNN model is used to improve the data fusion in WSN technologies. Finally, the improved WSN technologies are used to collect the actual traffic flow, but the cost is always very high. Therefore, the proposed FA-BPNN model is used to predict the actual traffic flow. Compared with the other three kinds of BPNN models, the proposed FA-BPNN model has the best effect and the shortest running time in the traffic flow prediction. In the future, we will adopt more advanced algorithms to improve the WSN technologies, use it to predict the traffic flow, and propose some important suggestions.

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Biography

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