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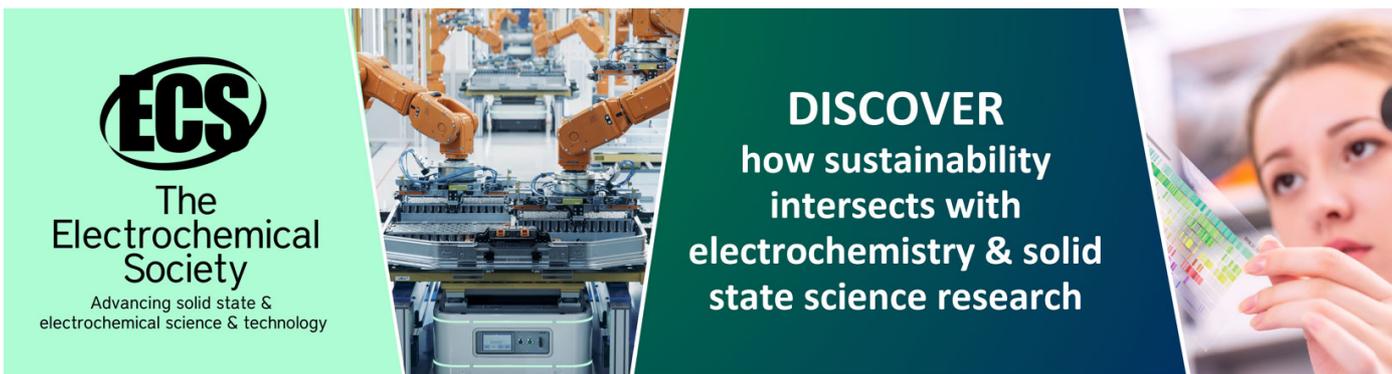
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Analysis of Temperature-induced Deflection of Cable-stayed Bridge Based on BP Neural Network

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Abstract. In order to study the relationship between ambient temperature and girder deflection quantitatively, realize the deflection prediction, a BP neural network deflection prediction method based on correlation analysis is proposed in this paper. The correlation between ambient temperature and girder deflection is analysed, and the BP neural network method is used to fit the samples with non-linear correlation quantitatively. Based on the quantitative relationship between ambient temperature and girder deflection, the prediction of girder deflection is realized. Taking Nanjing Yangtze River 3rd Bridge as an example, the feasibility of this method is verified based on monitoring data for four consecutive years. The results show that the non-linear mapping relationship between girder deflection at mid-span and ambient temperature is accurate and has good prediction effect. The method proposed in this paper provides a basis for the evaluation and early warning of the deflection.

1. Introduction

The large-span bridge plays an essential role in the national transportation system, and the decreasing of its safety and applicability jointly affected by heavy traffic load, wind, temperature, and other environmental factors cannot be neglected[1]. Therefore, it is vital for long-span bridges to evaluate the work indexes and to provide an early warning based on the monitoring data of long-term monitoring system [2].

Girder deflection is one of the most intuitive and effective indicators to reflect the overall performance of bridge structure. The deflection is monitored by the long-term monitoring system and affected by various external environmental factors during bridge service period, including temperature load, vehicle load, wind load, material performance degradation, pier subsidence, etc. The main factors affecting the girder deflection are temperature load and vehicle load. So it is necessary to eliminate the effects caused by the above factors for deflection evaluation and warning [3].

There are many types of research on concrete cable-stayed bridges, including the correlation analysis and quantitative fitting of the mapping relation. In the literature [5], the neural network is used to fit the mapping relation between the mid-span deflection and temperature in a concrete cable-stayed bridge. It is found that the deflection of concrete beam lags behind the temperature change. Literature [6] points out that there is a specific correlation between girder deflection and temperature on a composite cross-section cable-stayed bridge and there is a lag in mid-span deflection change. And the mapping relationship is quantified by the ARX model (Autoregressive Model of Exogenous Inputs).

However, there are few studies on the correlation between girder deflection and temperature of long-span cable-stayed bridges with all steel structure. The girder tower system with steel box section is radically different from the concrete girder tower system. The lag of girder deflection is less [7], and the correlation between girder deflection and temperature at all critical points should be considered at the



same time due to the excellent thermal conductivity of steel girder and tower. Besides, most of the studies are based on short-term monitoring data. Although it is sufficient to prove the correlation between deflection and temperature, the long-term effect of thermal deflection may be ignored. Therefore, the correlation between girder overall deflection and temperature of long-span cable-stayed bridges requires further research based on long-term monitoring data.

The BP neural network deflection prediction method based on correlation analysis is proposed in the paper. In order to realize the girder deflection prediction, the correlation analysis of girder deflection and ambient temperature is carried out, and the BP neural network method is used to fit the samples with non-linear relationship. Then, the paper takes Nanjing Yangtze River 3rd Bridge as example, and uses the monitoring data in four years to verify the feasibility of this method.

2. BP neural network deflection prediction method based on correlation analysis

2.1. *The characteristics of deflection induced by ambient temperature*

The change of ambient temperature complicates the composition and change of bridge response. In the cable-stayed bridge structure, the changing ambient temperature mainly influences the main girder, cables, and cable tower [3]. The change of ambient temperature causes not only the girder deformation but also the elastic deformation of cables and cable tower, thus affecting the girder alignment.

The elimination of ambient temperature-induced and vehicle-induced deflection contributes to deflection evaluation and dynamic warning in bridges [4]. Therefore, the quantification of ambient temperature effect on deflection is necessary to the bridge safety assessment.

2.2. *The methodology of correlation between deflection and temperature*

The specific relationship can be obtained based on the correlation analysis between deflection and ambient temperature. Then appropriate fitting methods can be used to fit the relationship between deflection and temperature quantitatively. In these ways, the temperature-induced deflection can be eliminated [8].

There are linear and nonlinear regression methods for the quantitative fitting of deflection-ambient temperature relationship. Linear regression methods include multiple linear regression method and parameterized linear ARX method, etc. Nonlinear methods include artificial neural network (ANN) method and support vector machine (SVM) method, etc. [9]

For the system with significant linear correlation, the linear regression method is used to fit the mapping relationship between sample data, which is simple, intuitive and effective. For a system with nonlinear correlation, the artificial neural network is often used to get the quantitative mapping relation between the sample data. A large number of monitoring data is needed to train the neural network and the final weights and thresholds of each layer are needed to determine. Then the mapping relationship can be simulated and the model validity can also be verified through data prediction, which is accurate and pertinent.

2.3. *Working principle and accuracy of parameters in BP neural network*

BP neural network, also known as error inverse propagation network, is composed of input layer, hidden layers and output layer. BP neural network has two main characteristics: the signal transmitting forward and error propagating backward. In forward transmission, the input signal enters from the input layer and processes to output layer through the hidden layer. BP network turns to propagate inversely if the output is undesirable, and the weights and thresholds adjust according to the predicted error. Therefore, the prediction output of BP neural network is constantly approximated to the expected output.

The BP neural network can be regarded as a nonlinear function. The independent variable of this function is the input value in the network, while the dependent variable of the function is the expected value, which means the BP neural network can express the mapping relationship between N input nodes (independent variables) and M output nodes (dependent variables). The basic process for studying the mapping relationship of sample system using BP neural network is shown in Figure 1 below. The

training steps include network initialization, output calculation in the hidden layer, and output calculation, error calculation, weight updating, threshold updating, etc.[10]

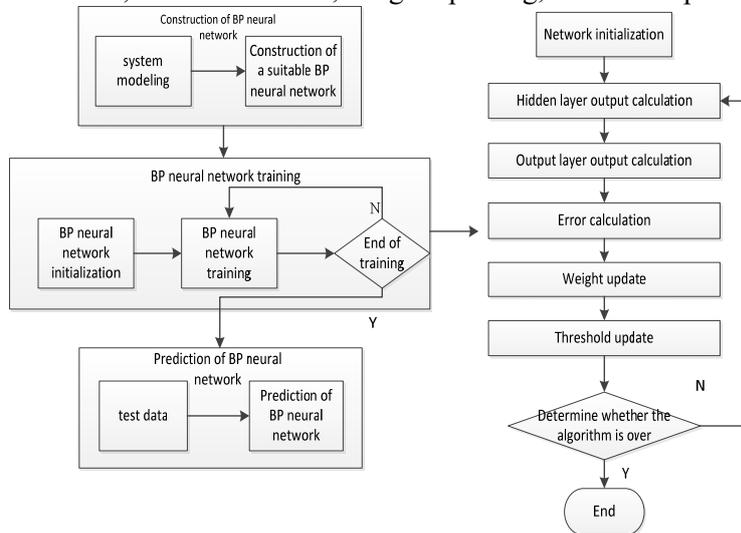


Figure 1. Basic working process of BP neural network

It can be seen from figure.1 that the factors influencing prediction accuracy in BP neural network include the number nodes in the input and output layer, the number of hidden layers, the number of nodes and transfer functions in the hidden layer, and the quantity of training data, etc. Besides, BP neural network has excellent ability in fitting functions with fewer input and output nodes. BP neural network with multiple hidden layers has strong generalization ability and high prediction precision, but the training time is longer. At the same time, it is necessary to notice that the prediction error may be significant when hidden layer nodes are exiguous, while the overfitting problem will appear when the nodes are excessive [11]. Also, having enough reliable training data is the fundamental guarantee for improving the prediction accuracy of BP neural network.

2.4. Research process in this article

In order to obtain the quantitative mapping relationship between deflection and ambient temperature, this paper proposes a BP neural network deflection prediction method based on correlation analysis. Then, this paper researches the monitoring data of ambient temperature and deflection on Nanjing Yangtze River 3rd Bridge in four consecutive years. The research process of this paper is shown in Figure 2. Firstly, the characteristics of bridge service are analysed to exclude the influence of other ambient factors; then a suitable period is selected to extract the monitoring data. Secondly, the long-term correlation between deflection and ambient temperature at different monitoring points is analysed based on monitoring data. Then proper methods are selected to fit the mapping relationship quantitatively based on correlation analysis, and the accuracy is examined. Finally, the quantitative relationship between girder deflection and ambient temperature is obtained.

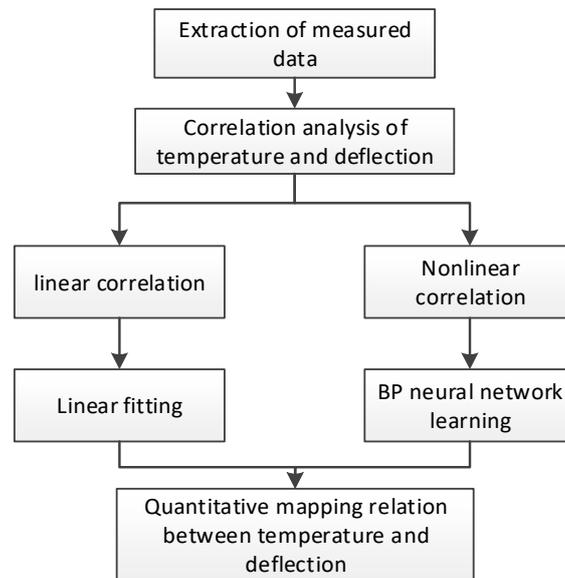


Figure 2. The research process of this paper

3. Correlation analysis of deflection and ambient temperature

This article selects Nanjing Yangtze River 3rd Bridge as the sampling bridge to study. The bridge is a semi-floating cable-stayed bridge with two cable planes, two steel towers, and steel box girder. The span arrangement is $63\text{m}+257\text{m}+648\text{m}+257\text{m}+63\text{m}=1288\text{m}$.

3.1. Monitoring data extraction

The long-term monitoring system includes temperature and humidity, wind speed, wind direction, strain, cable tension, tower tilt, deflection and dynamic structural characteristics subsystem. The ambient temperature sensors located in the No.0 girder block around South Tower.

The girder deflection is monitored by the pressure measurement method with closed pipes. The deflection at each monitoring point related to the base point is calculated based on the principle of hydraulic height difference and communicating pipe [12]. Taking the upstream side as example, there are 36 deflection sensors. These sensors are located at the anchorage area of each cable and beam, with the 10Hz sampling frequency. The distribution is shown in Figure 3. The change of deflection and ambient temperature is synchronized considering the material temperature sensitivity of the steel box girder [7]. As the reference station of deflection measurement is No. 0 girder block around the tower, the girder deflection is the value of each point relative to the base point.

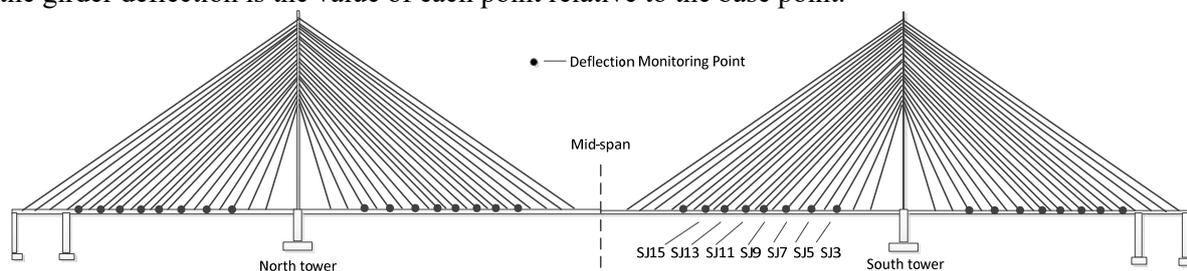


Figure 3. Sensor layout diagram of Nanjing No.3 Yangtze River Bridge

3.2. Correlation analysis of deflection and ambient temperature

According to figure 3, the bridge structure and sensor arrangement are symmetrical along the longitudinal bridge. The correlation analysis in this paper is based on the monitoring data at the south

tower side. Deflection is an essential index to the overall bridge characteristics, reflecting the general change. Therefore, the deflection at each monitoring point of the whole bridge should be analysed.

In order to study the correlation between deflection and ambient temperature, the research should exclude other ambient factors. At night, the change of ambient temperature is small and holistic. At the same time, the statistics show that the average value of constant load deflection after the elimination of vehicle influence is very close to the average value of the monitoring deflection from 0 o'clock to 1 o'clock [7]. This article takes the average of deflection and temperature from 0 o'clock to 1 o'clock in 2007,2008 and 2009 as research data. The scatter plot of the temperature and deflection is shown in Figure 4.

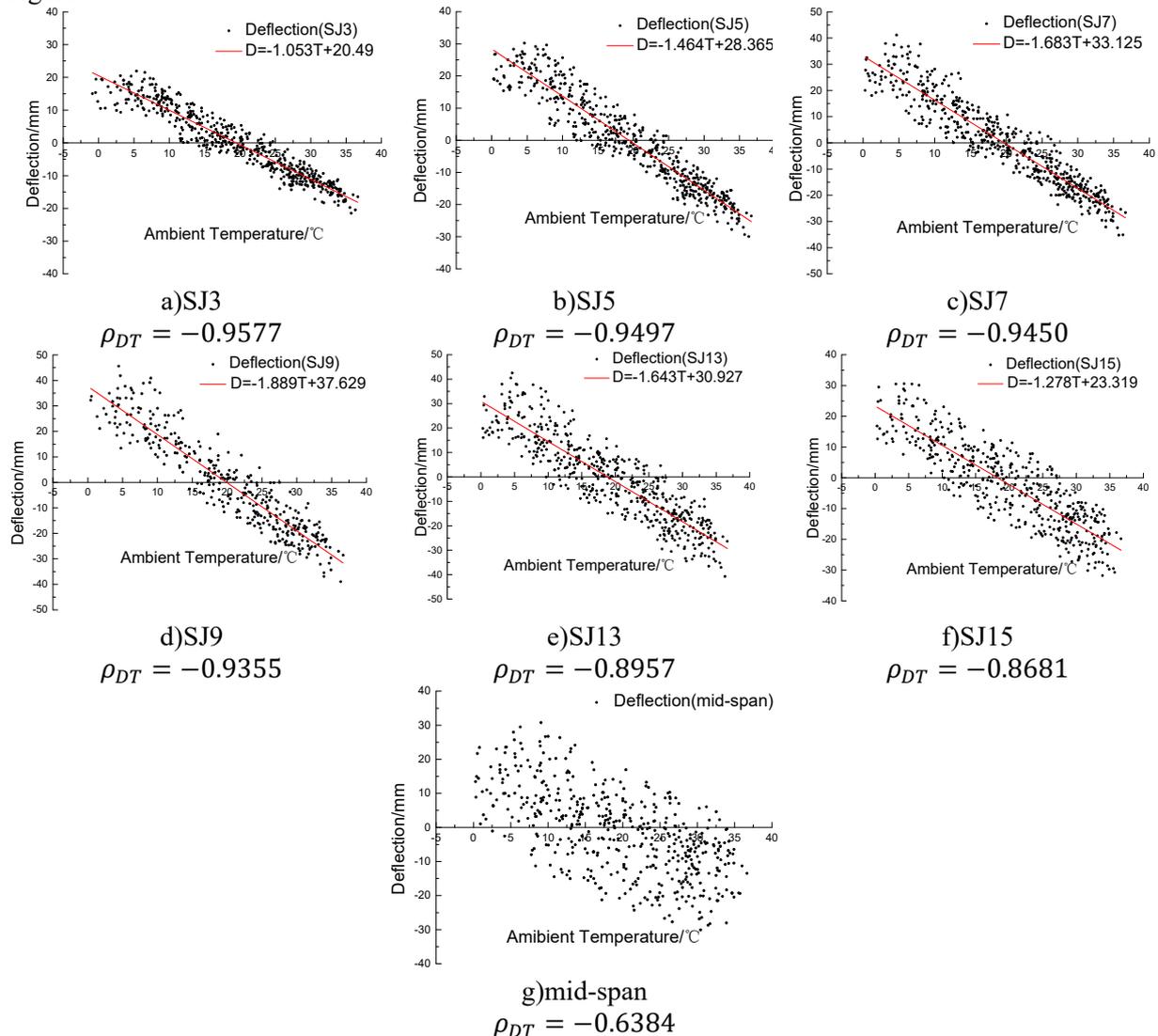


Figure 4. The correlation of deflection and ambient temperature at different monitoring points

Figure 4 shows that deflection at the SJ3, SJ5, SJ7, SJ9, SJ13, SJ15 monitoring points are negatively correlated with ambient temperature and the linear correlation is strong. The minimum absolute value of correlation coefficient is 0.868. The linear correlation of the girder deflection at mid-span is weak with $\rho_{DT} = -0.6384$ [13].

3.3. Quantitative relationship fitting between deflection and ambient temperature

The deflection is highly linear correlated to ambient temperature at monitoring points near the tower and the quarter of girder (near the SJ9 monitoring point), including the SJ3, SJ5, SJ7, SJ9, SJ13, SJ15

monitoring points. The vehicle-induced deflection is submerged in ambient temperature-induced deflection in long-term. Therefore, the linear fitting method can be used to fit the relationship between deflection D (mm) and ambient temperature T ($^{\circ}\text{C}$) at these monitoring points. The fitting results are shown in Table 1.

Table 1. Fitting results of temperature and girder deflection.

Location	Linear fitting coefficient (A)	Linear fitting result	Linear correlation coefficient (R^2)
SJ3	-1.053	$D = -1.053T + 20.490$	0.9120
SJ5	-1.464	$D = -1.464T + 28.365$	0.9017
SJ7	-1.683	$D = -1.683T + 33.125$	0.8927
SJ9	-1.889	$D = -1.889T + 37.629$	0.8728
SJ13	-1.642	$D = -1.642T + 30.927$	0.8019
SJ15	-1.278	$D = -1.278T + 23.319$	0.7531

Note: as shown in Figure 3, SJ n ($n=3, 5, 7, 9, 13, 15$) is the monitoring point n on girder

The above table shows that the correlations between deflection and ambient temperature have a strong linear relationship, and the linear correlation coefficient (R^2) at each monitoring point is more than 0.75. So the relationship between deflection and ambient temperature can be accurately fitted by linear fitting method.

In addition, from a long-term perspective, the effect of ambient temperature on deflection has obvious regularity. The absolute value of the linear fitting coefficient (A) is the maximum at the quarter of girder. For example, the linear fitting coefficient $A = -1.889$ at the SJ9 monitoring point meaning the deflection will increase $1.889\text{mm}/^{\circ}\text{C}$. While the linear fitting coefficient $A = -1.053$ at the SJ3 monitoring point meaning the deflection will increase $1.053\text{mm}/^{\circ}\text{C}$. So the deflection at the quarter is the most sensitive to ambient temperature. The absolute value of the linear fitting coefficient (A) becomes smaller with the further distance between the monitoring point and the quarter. That means the temperature sensitivity of deflection is lower at the monitoring points near tower and mid-span.

4. Deflection prediction at mid-span using BP neural network

According to the correlation analysis, the ambient temperature sensitivity of deflection is low near the mid-span and the long-term thermal effect on girder deflection is submerged in vehicle-induced deflection. This phenomenon attributes to the nonlinear variation of cable length with ambient temperature [14]. So the linear regression method cannot accurately fit the relationship between deflection and ambient temperature at mid-span. Considering the small correlation coefficient between the ambient temperature and deflection, the relationship is fitted using BP neural network method quantitatively. In order to exclude vehicle-induced deflection, this paper selects the monitoring data during bridge closure period in four years.

When training the BP neural network, this article constructs the single input-output system by taking the ambient temperature as input and the mid-span deflection as output. The optimized BP network with the three hidden layers including 20 nodes is selected for training. The transfer function in the hidden layer selects the 'logsig' type, and the transfer function in the output layer selects the 'tansig' type [10]. In the monitoring data during bridge interdiction period, 950 pairs are randomly selected as the sample data for training (shown in Figure.5), and 45 pairs are used for prediction and verification. The predicted result is shown in Figure 6. The abscissa is the number of samples, and the ordinate is the relative deflection (mm) at mid-span.

From Figure 6, it can be seen that the maximum error of simulation result is 1.85mm , the relative error is 7.89% , and the relative error of the 45 pairs of predicted values is within 8% , with $R^2 \approx 0.95$. It is proved that the relationship between the girder deflection and ambient temperature at mid-span is fitted reliably by BP neural network training.

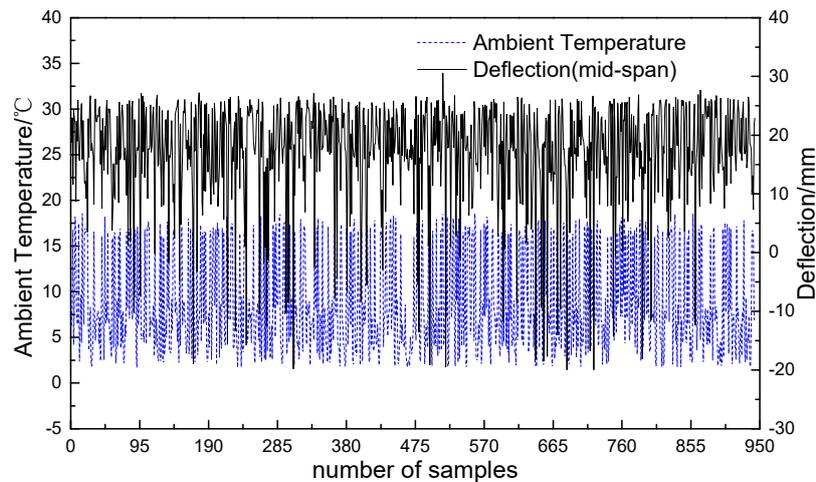


Figure 5. Training data in BP Neural Network

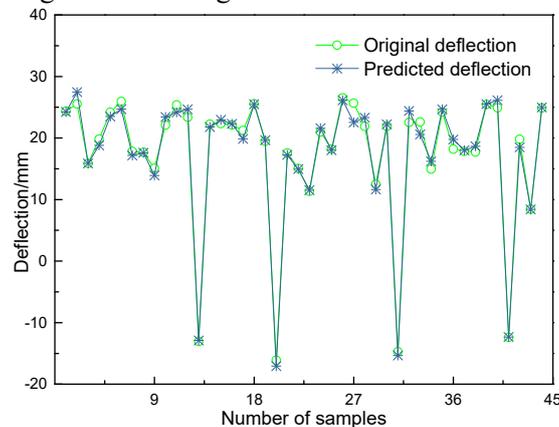


Figure 6. BP Neural Network Training results of deflection at mid-span

5. Conclusion

In order to predict the ambient temperature-induced deflection of a cable-stayed bridge, a BP neural network method based on correlation analysis is proposed to quantitatively analyse the relationship between deflection and ambient temperature. This paper takes Nanjing Yangtze River 3rd Bridge as an example, and obtains the following conclusions.

(1) The linear correlation between deflection and ambient temperature is strong at the monitoring points near tower and the quarter of girder, and the linear correlation is weak at the monitoring points at mid-span. The deflection is significantly influenced by ambient temperature near tower and the quarter of girder and by vehicle at mid-span.

(2) The relationship between deflection and ambient temperature near tower and the quarter of girder can be accurately fitted by linear fitting method. It is found that the ambient temperature sensitivity of deflection is the highest at the quarter of girder by comparing the linear fitting coefficients. And the ambient temperature sensitivity of deflection is sure correlated with the distance between monitoring points and the girder quarter. The further the distance is, the less sensitive deflection is to ambient temperature.

(3) Based on the weak linear correlation with ambient temperature and the high vehicle sensitivity of deflection, this paper takes the monitoring data during bridge closure period to exclude the influence of vehicle. The BP neural network is used to fit the relationship between deflection and ambient temperature at mid-span. And for the known ambient temperature, deflection at mid-span can be accurately predicted.

(4) This paper analyses the correlation between deflection and ambient temperature based on the long-term monitoring data, and obtains the quantitative relationship between deflection and ambient temperature. This paper also proposes a reliable method to extract the temperature-included deflection from monitoring data. The above study can provide a foundation for the following researches of deflection early warning in cable-stayed bridges.

Acknowledgments

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