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Predict typhoon-induced storm surge deviation in a principal component back-propagation neural network model*

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Abstract To reduce typhoon-caused damages, numerical and empirical methods are often used to forecast typhoon storm surge. However, typhoon surge is a complex nonlinear process that is difficult to forecast accurately. We applied a principal component back-propagation neural network (PCBPNN) to predict the deviation in typhoon storm surge, in which data of the typhoon, upstream flood, and historical case studies were involved. With principal component analysis, 15 input factors were reduced to five principal components, and the application of the model was improved. Observation data from Huangpu Park in Shanghai, China were used to test the feasibility of the model. The results indicate that the model is capable of predicting a 12-hour warning before a typhoon surge.

Keyword: typhoon; storm surges forecasts; principal component back-propagation neural networks (PCBPNN); Changjiang (Yangtze) River estuary

1 INTRODUCTION

Typhoon is a type of strong tropical cyclone generated in a tropical ocean, and is often accompanied by strong wind, heavy rain, and even storm flood. A typhoon making landfall can bring 100–300 mm, and sometimes 500–800 mm rainfall in just one day, and also the storm surge (abnormal rise of the water level near the coast) which make the coastal tide rise 5–6 m because of the strong wind and low pressure. It is even worse when the storm surge coincides with the astronomical high tide, which will cause higher water levels which will overflow to destroy the houses, farms and cities, and result in heavy casualties and property losses (Zhang and Cao, 1992).

In order to decrease the losses of casualties and properties caused by typhoon, the forecast of typhoon and storm tide is essentially important. Conventional methods for predicting the storm tide mainly include two types (Li, 1993). One is the empirical method and the other is the numerical model. To forecast the storm surge, Hansen (1956) presented a numerical model of fluid dynamics to apply to the North Sea. Kawahara et al. (1982) proposed a two-step explicit finite element method to analyze the storm surge propagation. Jelesnianski and Shaffer (1992) applied the SLOSH model (Sea, Lake and Overland Surge from Hurricane) to forecasting the storm surge. However, given the complexity of typhoon effect, specified typhoon models, accurate and detailed hydrodynamic equations, coastal topographical data, boundary

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conditions, weather forecast, and elaborate and time-consuming calculations are needed for the numerical simulation models (Abohadima and Rabie, 2002; Tseng et al., 2007). Unfortunately, the efficiency and accuracy of numerical simulation cannot meet the requirement of typhoon surge forecasting in the absence of accurate and detailed topographical data and boundary conditions. Jan et al. (2006) attempted to establish empirical formulas for typhoon surge estimation according to the statistical analysis of the correlation between typhoon surge deviations and typhoon characteristics. To make use of the superiority of artificial neural networks (ANN) in overcoming the problem of exclusive and nonlinear relationships, Lee (2008) used back-propagation neural networks (BPNN) to establish a typhoon-surge forecasting model and predicted short-term typhoon surges considering typhoon parameters (wind speed, wind direction, central pressure) and astronomical tidal level as the input factors. In addition, You and Seo (2009) developed a cluster neural network model (CL-NN) to predict storm surges in all Korean coastal regions by combining neural network with agglomerative clustering.

In this research, a typhoon surge-deviation forecasting model is developed using a principal component back-propagation neural networks (PCBPNN). The forecasting model includes the upstream flood caused by typhoon rainfall and the historical surge deviation, as well as the typhoon characteristics. The tidal level data from Huangpu Park observation station in Shanghai, China are used to test the performance of the proposed PCBPNN model.

2 METHOD AND APPLICATION

With the capability to model both linear and nonlinear systems without the need to make any assumptions which are implicit in most traditional statistical approaches, some researches on the applications of ANN into forecasting the storm surge aim at integrating correlative factors influencing the typhoon storm surge, such as the surge, rainfall and flooding caused by a typhoon (Xue et al., 2005; Lee, 2006, 2009; Li et al., 2006; Tseng et al., 2007; Bajo and Umgiesser, 2010). A typical three-layer network includes an input layer (I), a hidden layer (H) and an output layer (O). Each layer consists of several neurons that are connected by weights, thresholds, and transfer functions. To remove redundant information and raise the efficiency of computation,

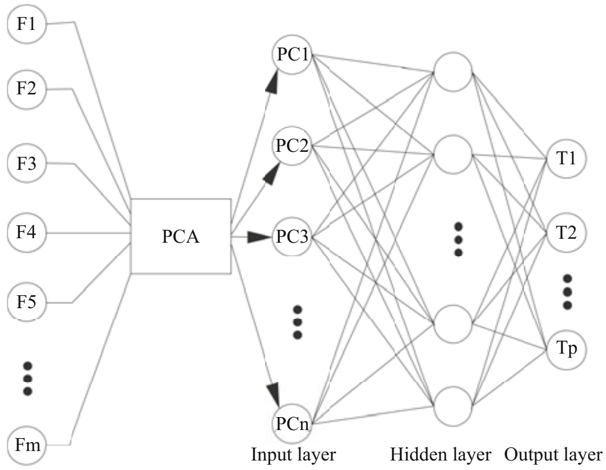

Fig.1 Structure of principal components back-propagation networks model

Fm represent the factors influencing typhoon surges, PCn represent the principal components, and Tp represent the target.

the PCBPNN model is used to predict the typhoon induced surge deviation (Fig.1). The typhoon surge deviation at a time in a considered tidal station during a typhoon event can be expressed as the difference between the measured sea water level and the estimated astronomical tide level (Tseng et al., 2007). In the PCBPNN model, the data set of input factors is processed with principal component analysis (PCA) so that a set of uncorrelated principal components (PCs) can stand for most of information which original input factors contain and the dimension of the input data set can be reduced.

Assuming that we have p samples and m factors, making a $p \times m$ matrix $\boldsymbol{F}$:

$$\boldsymbol{F}=[F_1, F_2, ..., F_m], \tag{1}$$

By means of PCA, the original matrix $\boldsymbol{F}$ is transformed to the matrix composed of PCs that are the linear combination of the original factors. Then the transformed matrix is taken as the input into the network. During the first phase in the network training process, the input is propagated forward through the network to compute the output values. This computed output is compared with its corresponding desired output, resulting in an error for each output unit. During the second phase, the errors in the output layer are propagated backward to the input layer through the hidden layer and the weights of connection are calculated and adjusted to minimize the output errors using the gradient descent method.

The error function of the output neurons is defined as:

$$E=\frac{1}{2}\sum_{j=1}^{n}(T_j-O_j)^2 , \tag{2}$$

where T_j and O_j are the values of the target and output, respectively, and n is the number of neurons in the output layer. More details of the BPNN algorithm can be referred to the literatures (Fausett, 1994; Bishop, 1995; Rumelhart et al., 1986; Zhou and Kang, 2006). Because the BP algorithm has a low performance in training process, to accelerate the convergence of the error in the learning procedure, the momentum term with the momentum gain α is included in the error modification process:

$$\omega_{ij}(k+1) = \omega_{ij}(k) + \eta[(1-\alpha)D(k) + \alpha D(k-1)], \quad (3)$$

where $D(k)$ and $D(k–1)$ are the negative gradient at time k and time $k–1$, respectively, η is the learning rate, α is momentum gain in the interval of [0, 1], and ω_{ij} is the weight connected the ith neuron in the input layer with the jth neuron in the hidden layer. At the same time, adaptive learning rate is also adopted to adjust the learning rate and increase the stability of the model.

Evaluation of the performance of a typhoon induced storm surge forecasting model should not only depend on the overall or average errors, but also on errors of the greatly high tide level (when the high tide is greater than 4.5 m) and the greatly high storm surge deviation (when the storm surge deviation is greater than 0.5 m), because they always cause more serious damages than normal tide. The three criteria involved in model performance evaluation are as follows:

(1) Root mean square error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(T_t - T_t')^2}, \quad (4)$$

where T_t is the forecasted storm surge deviation, T_t' is the observed storm surge deviation, and n is the number of neurons in the output layer.

(2) Coefficient of correlation (CC)

$$\text{CC} = \sum_{t=1}^{n}(T_t - \overline{T}_t)(T_t' - \overline{T}_t') \Big/ \sqrt{\sum_{t=1}^{n}(T_t - \overline{T}_t)^2 \sum_{t=1}^{n}(T_t' - \overline{T}_t')^2}, \quad (5)$$

where $\overline{T}_t$ is the average of forecasted storm surge deviation, and $\overline{T}_t'$ is the average of observed storm surge deviation.

(3) Coefficient of efficiency (CE)

$$\text{CE} = 1 - \left(\sum_{t=1}^{n}(T_t - T_t')^2 \Big/ \sum_{t=1}^{n}(T_t - \overline{T}_t)^2\right), \quad (6)$$

CE is used to evaluate the model performance, and CE of 1 indicates perfect forecast.

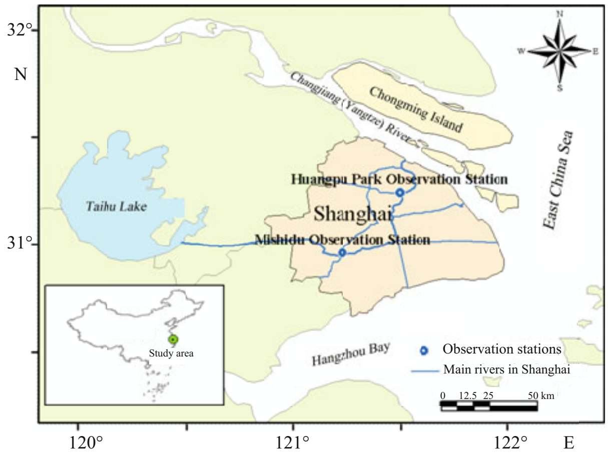

Fig.2 Map of study area and observation stations

2.1 Study area and data collection

Shanghai is the biggest city in China, and it faces the East China Sea and lies to the east of the Taihu Lake, the south of the Changjinag (Yangtze) River estuary, and the north of Hangzhou Bay. The city is prone to storm-flooding caused by storm surge and rainfall due to the distribution of typical tidal estuary and plain river network. Affected by the East Asian monsoon, Shanghai suffers from 2–3 typhoons annually in summer. The city's infrastructure, people's lives, and properties are often threatened greatly by the meeting of strong wind, heavy rain, storm surge, and flood from the upper stream area. Crossing the central city, the Huangpu River is the main channel for the waters of Taihu Lake entering the Changjiang River, and it carries 78% of the Taihu Lake's drainage. We select Huangpu Park observation station as the target station because it is located at the central region of Shanghai and its water level is of importance to the safety of Shanghai city. Located at the upstream of Huangpu River, Mishidu observation station is 55.5 km distant from Huangpu Park observation station. The maximum speed of water flow in Huangpu River is 1.8 m/s when the tide ebbs, that is, it takes almost 11 hours for the flood to flow from Mishidu observation station to Huangpu Park observation station (Fig.2). There were 26 typhoons influencing Shanghai between 1999 and 2008, and we collected the typhoon characteristics (such as longitude, latitude, central pressure, maximum typhoon-near-center wind velocity, forward speed, and heading) every 6 hours, and the tidal information (such as astronomical high tidal level, observed high tidal level, and empirically forecasted high tidal level, etc.)

in Mishidu observation station and Huangpu Park observation station twice in one day during the typhoon events in Shanghai. Based on the PCBPNN, the typhoon-induced storm surge forecasting model is constructed and validated using the collected data.

2.2 Determination of influencing factors and data preprocessing

Possible factors influencing typhoon surges include typhoon characteristics, local geographical characteristics and local meteorological condition in the vicinity of a particular tidal observation station (Tseng et al., 2007). The changes of typhoon characteristics and the local meteorological conditions at a given tidal station during a typhoon event are significant, while the change of local geographical characteristics is usually small and negligible. Therefore, in this research, a PCBPNN-based typhoon-induced surge forecasting model is developed according to the typhoon characteristics and local meteorological conditions.

Considering the typhoon is a dynamic process, two series of typhoon characteristics before the forecasting time (t), i.e., the typhoon characteristics at the time of t-12 and t-18, are taken into account. In addition, six typhoon characteristics are taken in the study, including the longitude ($F1$, $F7$), latitude ($F2$, $F8$), central pressure ($F3$, $F9$), maximum typhoon-near-center wind velocity ($F4$, $F10$), forward speed ($F5$, $F11$) and heading ($F6$, $F12$). As the target station's historical surge deviations inevitably influence the forecast of surge deviations, the historical surge deviations at the time of t-12 ($F13$) and t-24 ($F14$) are also taken into account. In the meantime, the historical storm surge deviations at the time of t-12 in Mishidu observation station ($F15$), which measure the height of surges above the astronomical tide relating to the upstream flood caused by typhoon rainfall, are considered. The target (T) in the output layer of the PCBPNN model is the typhoon surge deviation at the forecasting time (t) in the target observation station of Huangpu Park station.

We collect the typhoon data from 1999 to 2008, as well as storm flood data at the Huangpu Park observation station and Mishidu observation station during the same period. 251 grouped observations of the 15 variables extracted from the data of influencing factors from 1999 to 2006 are taken as the PCBPNN training sample, and 51 grouped observations of the 15 variables extracted form the data from 2007 to 2008 are taken to test the model. The values of the

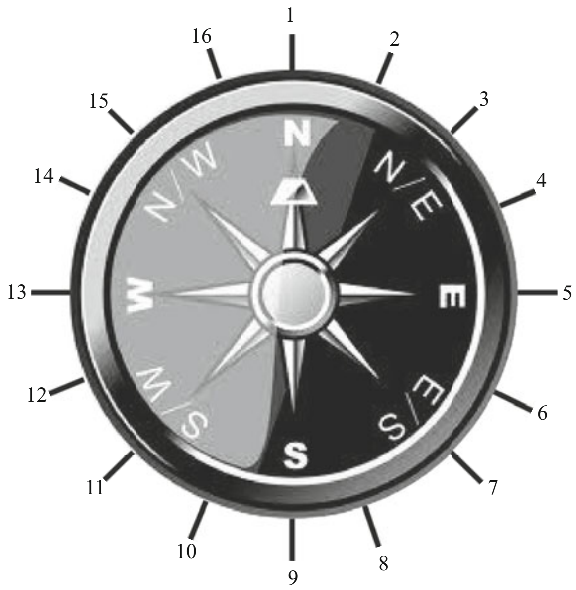

Fig.3 Representative values of typhoon headings that divided into 16 bearings

above-mentioned factors are standardized to eliminate the effect of different units, using the standard deviation equation:

$$X'_{ij} = (X_{ij} - \overline{X_j}) / s_j , \tag{7}$$

where X_{ij} is the original value of the ith observation of the jth variable, $\overline{X_j}$ is the average value for each column of the data matrix X_{ij}, s_j is the standard deviation, and X'_{ij} is the standardized value.

For the typhoon heading ($F6$, $F12$), we take the north direction as 1, and all headings are transferred to 1–16 in clockwise order. The headings are divided into 16 bearings as shown in Fig.3.

Table 1 shows the correlation coefficients between the input factors ($F1$–$F15$) and the target (T). The historical surge deviations at the Huangpu Park observation station ($F13$, $F14$) have significant positive correlations with the target (T), and the correlation coefficients are 0.757 and 0.824, respectively. The historical surge deviations at the upstream station ($F15$), the Mishidu observation station, also have a positive correlation with the target (T), although the correlation coefficient is smaller than those between $F13$, $F14$ and T. A single typhoon characteristic ($F1$–$F12$) has a low degree of correlation with the target (T), but the research (Jan et al., 2006; Lee, 2006) indicated that typhoon characteristics were the major factors influencing the surge deviation, and the potential influences of the typhoon characteristics on the surge deviation still need to be investigated.

2.3 Model construction

The PCBPNN model is constructed to predict the typhoon-surge deviation 12-h ahead at the Huangpu Park observation station. After PCA is performed, the 15 input factors are transformed into 5 principal components, which contain more than 95% information of the original factors. An optimal neural network structure is important to the performance of the typhoon-surge deviation forecasting. The adjustment of the model's parameters is essential to increase the accuracy of the forecast. The parameters include the number of the hidden layer's neurons, the learning rate (η), the momentum factor (α), and the training epochs. Table 2 presents the performance of different model structures using different combinations of the parameters. When designing the number of the hidden layer's neurons, we refer to the following empirical equation (Zhou and Kang, 2006):

$$S=\sqrt{R+S^{L}}+a\,, \tag{8}$$

where S is the number of neurons in the hidden layer, R is the number of neurons in the input layer, S^L is the number of neurons in the output layer, and a is an integral constant in the interval of [0, 10], which is fixed by trial and error. In this study, the number of the input layer's neurons is fixed to five, and the number of the output neuron is one, so the S is in the interval of [3, 13]. We select different numbers of hidden neurons (such as 4, 6, 8, 10, and 12), learning rate (η), and momentum factor (α) for trying, and find that when S is set to 10, η is 0.01 and α is 0.9, the model has the optimal performance according to the index of RMES, CC and CE. In addition, the experiment results show that the increase of the epochs from 5 000 to 10 000 cannot improve the performance of the model. Consequently, we determine the parameters, i.e., S=10, η=0.01, α=0.9 and Epochs=5 000 for the optimal model structure. Fig.4 illustrates the training process of PCBPNN model for typhoon surge deviation forecast, and this model is tested using the observations of the 15 variables extracted from the data from 2007 to 2008.

Table 1 Correlation coefficients between the factors and the target

Factors	$F1$	$F2$	$F3$	$F4$	$F5$
Correlation coefficients with target (T)	0.097	0.176	-0.149	0.167	0.056
Factors	$F6$	$F7$	$F8$	$F9$	$F10$
Correlation coefficients with target (T)	0.021	0.106	0.181	-0.128	0.143
Factors	$F11$	$F12$	$F13$	$F14$	$F15$
Correlation coefficients with target (T)	0.102	-0.018	0.757	0.824	0.409

Table 2 Performance of different model structures

Numbers of hidden neurons	η	α	Epochs	RMSE (m)	CC	CE
4	0.01	0.9	5 000	0.170 0	0.860 0	0.700 0
6	0.01	0.9	5 000	0.150 0	0.890 0	0.770 0
8	0.01	0.9	5 000	0.150 0	0.900 0	0.800 0
10	0.01	0.9	5 000	0.137 8	0.921 4	0.840 2
12	0.01	0.9	5 000	0.160 0	0.890 0	0.790 0
10	0.01	0.6	5 000	0.147 4	0.904 8	0.805 1
10	0.01	0.3	5 000	0.168 2	0.879 8	0.761 9
10	0.05	0.9	5 000	0.146 9	0.908 6	0.813 0
10	0.10	0.9	5 000	0.166 1	0.877 5	0.753 5
10	0.30	0.9	5 000	0.157 0	0.900 3	0.800 3
10	0.01	0.9	10 000	0.142 4	0.911 8	0.823 2

3 RESULT AND DISCUSSION

Two standards are used to evaluate the prediction quality, namely the passing rate and the average error. The passing rate is the percentage of the qualified predicting number to total predicting number, which was defined by the National Standardizing Committee, China in 2009, and calculated using the following equations:

$$\mathrm{QR}=(m/n)\times 100\%, \tag{9}$$

where QR is the passing rate, m is qualified predicting number, and n is total predicting number. According to the output of the testing samples, the passing rate of PCBPNN model is 85.43%, which is satisfactory. In addition, the average error is calculated as follows:

$$E_{\mathrm{MA}}=\frac{1}{n}\sum_{t=1}^{n}\left|T_t-T_t'\right|, \tag{10}$$

where the E_{MA} is the average error, T_t and T_t' are the forecasted and observed storm surge deviation, respectively. The average error of all the samples is 0.120 m, and the average errors of the training sample and the testing sample are 0.110 m and 0.136 m, respectively (Figs.5 and 6). In addition, the average errors of the great tide (tide level>4.5 m) and the great surge deviation (surge deviation>0.5 m) are 0.148 m and 0.137 m, respectively, which are important to flood prediction.

The major contributing factors to each principal component can be discovered according to the

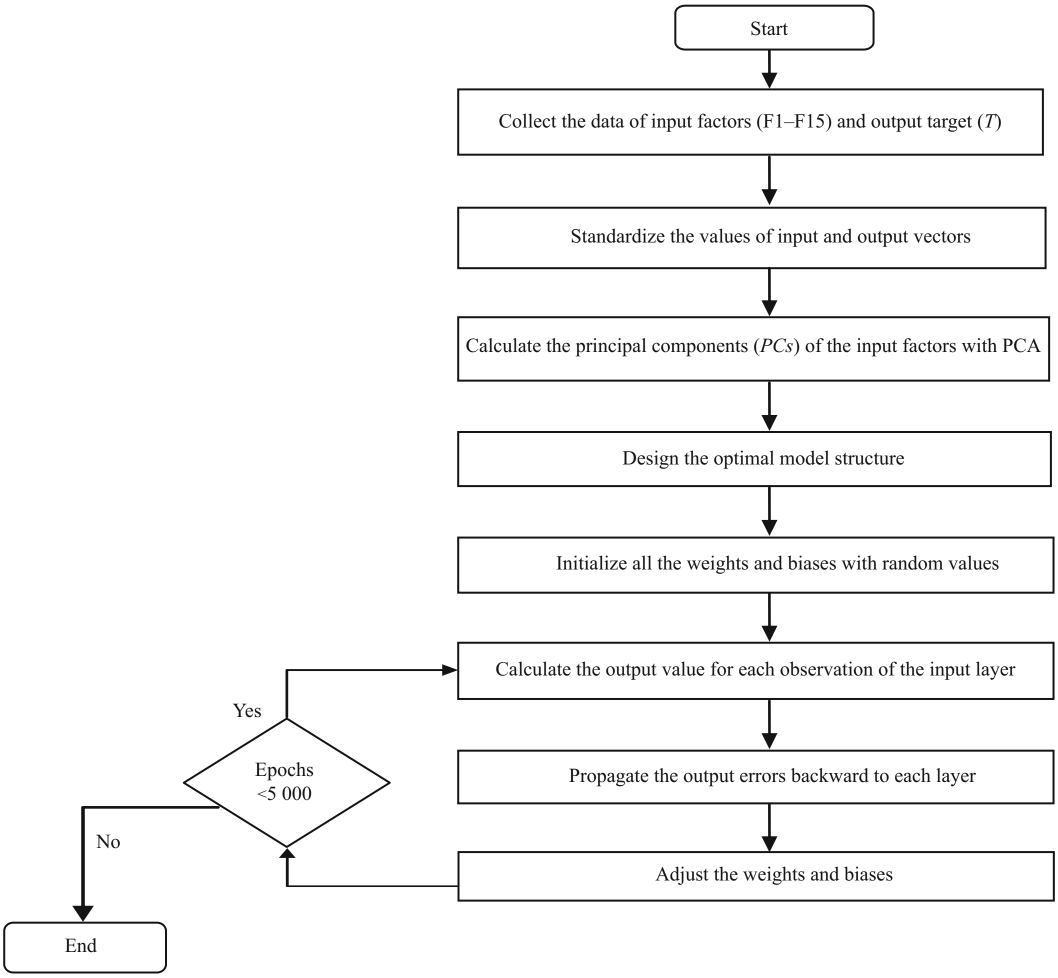

Fig.4 Flow chart of training process of PCBPNN model for typhoon surge deviation forecast

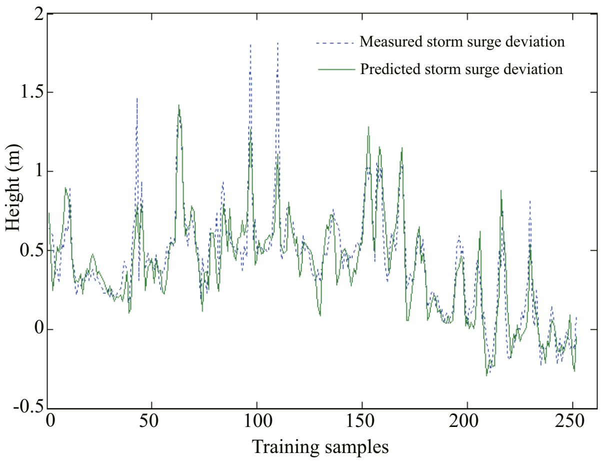

Fig.5 Difference between measured and predicted storm surge deviation with PCBPNN model on training samples

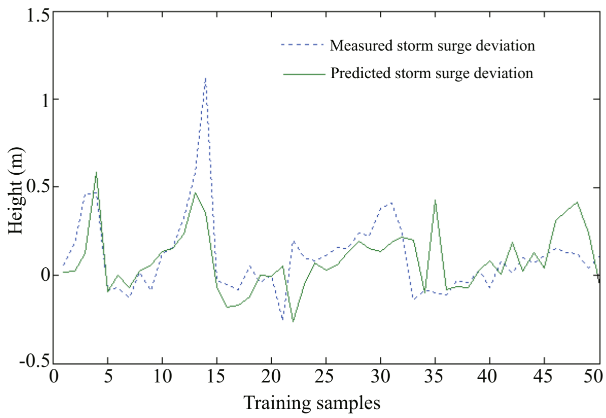

Fig.6 Difference between measured and predicted storm surge deviation with PCBPNN model on testing samples

principal component score coefficient matrix presented in Table 3. The PC1 mainly represents the information of the typhoon characteristics such as typhoon location ($F1$, $F7$), central pressure ($F3$, $F9$) and maximum typhoon-near-center wind velocity ($F4$, $F10$), PC2 also represents the location of typhoon ($F1$, $F7$), central pressure ($F3$, $F9$), and maximum typhoon-near-center wind velocity ($F4$, $F10$), PC3 represents the location of typhoon ($F2$, $F8$) and the

Table 3 Principal component score coefficient matrix

	$F1$	$F2$	$F3$	$F4$	$F5$
PC1	-0.300	0.264	-0.317	0.312	-0.146
PC2	0.338	-0.163	-0.372	0.376	0.211
PC3	0.106	-0.409	-0.075	0.082	-0.180
PC4	0.052	-0.204	0.007	0.018	-0.542
PC5	-0.053	0.163	-0.076	0.079	-0.301
	$F6$	$F7$	$F8$	$F9$	$F10$
PC1	0.292	-0.306	0.253	-0.352	0.353
PC2	-0.116	0.343	-0.162	-0.331	0.328
PC3	0.072	0.097	-0.416	-0.077	0.076
PC4	0.112	0.036	-0.207	0.024	-0.010
PC5	-0.610	-0.059	0.190	-0.089	0.097
	$F11$	$F12$	$F13$	$F14$	$F15$
PC1	-0.143	0.303	-0.055	-0.026	-0.122
PC2	0.220	-0.148	0.147	0.180	0.192
PC3	-0.203	0.070	-0.480	-0.466	-0.291
PC4	-0.548	0.040	0.324	0.345	0.277
PC5	-0.205	-0.560	0.005	-0.085	-0.277

Table 4 Weights between the input factors and the output neuron

Principal components	PC1	PC2	PC3	PC4	PC5
Weights	0.587 7	0.426 9	0.339 1	0.480 9	0.493 4

historical surge deviations information ($F13$, $F14$, $F15$), PC4 stands for the forward speed of typhoon ($F5$, $F11$) and the historical surge deviations ($F13$, $F14$, $F15$), and PC5 represents the heading of typhoon ($F6$, $F12$).

The weights between the neurons in the input layer and the neurons in the output layer are presented in Table 4, which reflect the degree of impacts of the five input factors on the output. It can be seen that the weights of the five PCs are almost equal, while the PC1 has relatively high degree of impacts on the output. Thus, the typhoon characteristics are key factors to forecast the surge deviation, especially the location of typhoon which also contributes to the PC2 and the PC3, heading which also contributes to the PC5, central pressure, and maximum typhoon-near-center wind velocity. In the meantime, the historical surge deviations in the target observation station and the upstream observation station, which contribute to the PC3 and the PC4, also influence the accuracy of predicting the typhoon induced storm surge deviation in the target station.

4 CONCLUSION

Due to the stochastic nature and complexities of wind inducing surge, the physical mechanism of storm surge generation is far from being understood at present. Conventionally empirical methods or numerical forecasting models for typhoon induced storm surge forecast are time-consuming and unable to include all influencing factors. Therefore, the development of novel effective approaches to forecasting accurate typhoon induced storm surge is an important task to alleviate significant damage to life and property in coastal areas. In this research, an alternative principal components back-propagation neural network (PCBPNN) model is constructed for typhoon surge deviation forecast, which takes into account not only the impact of typhoon wind characteristics on the surge, but also that of the rainfall and the upstream flood. With comprehensive factors, the proposed model has performed well in forecasting the typhoon surge deviation 12-h ahead when it is applied to Shanghai, a coastal city in China. The results indicate that the PCBPNN model is capable of typhoon surge deviation forecasting. Moreover, the historical surge deviations in the target station and the upstream station, and the typhoon characteristics, especially the location, central pressure and maximum typhoon-near-center wind velocity, are found to be the major determinant factors in the typhoon surge deviation forecast.

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