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Displacement prediction in geotechnical engineering based on evolutionary neural network

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Abstract. It is very important to study displacement prediction in geotechnical engineering. Nowadays, the grey system method, time series analysis method and artificial neural network method are three main methods. Based on the brief introduction, the three methods are analyzed comprehensively. Their merits and demerits, applied ranges are revealed. To solve the shortcomings of the artificial neural network method, a new prediction method based on new evolutionary neural network is proposed. Finally, through two real engineering applications, the analysis of three main methods and the new evolutionary neural network method all have been verified. The results show that, the grey system method is a kind of exponential approximation to displacement sequence, and time series analysis is linear autoregression approximation, while artificial neural network is nonlinear autoregression approximation. Thus, the grey system method can suitably analyze the sequence, which has the exponential law, the time series method can suitably analyze the random sequence and the neural network method almostly can be applied in any sequences. Moreover, the prediction results of new evolutionary neural network method is the best, and its approximation sequence and the generalization prediction sequence are all coincided with the real displacement sequence well. Thus, the new evolutionary neural network method is an acceptable method to predict the measurement displacements of geotechnical engineering.

Keywords: displacement prediction; geotechnical engineering; grey system; time series analysis; artificial neural network; evolutionary neural network

1. Introduction

Geotechnical engineering is one natural geological engineering. The understanding of the geotechnical engineering is only limited to the performance of its appearance. Thus, the deformation displacement is the direct appearance performance of the geotechnical engineering. It can be said that the displacement sequence contains all information pertaining to the development and evolution of the geotechnical engineering. Therefore, the study of the displacement of geotechnical engineering is the foundation for stability analysis. Moreover, because the displacement can be monitored easily, the analysis of measurement displacement is used in many

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geotechnical engineering for a long time. The New Austria Tunnelling Method (NATM) is one famous construction method for geotechnical engineering based on analysis of measurement displacement. The real engineering practice prove that it is very important to predict the measurement displacement. Therefore, researchers have always attached great importance to study the displacement prediction of geotechnical engineering; many studies have been conducted, including the curve fitting method or the empirical formula method (Angin 2016, Bozzano *et al.* 2014, Haeri and Sarfarazi 2016, Liu *et al.* 2015, Mazek 2014, Zhang and Goh 2016), grey system method (Li *et al.* 2005, Liu *et al.* 2009, Lu and Rosenbaum 2003), time series analysis method (Huang *et al.* 2003, Qiao and Zhao 2011), the artificial neural network (ANN) method (Aktas and Ozerdem 2016, Aleshin and Torgoev 2013, Bizjak and Petkovšek 2004, Chen and Zeng 2013, Chen *et al.* 2015, Chen *et al.* 2015, Lai *et al.* 2016, Lu and Rosenbaum 2003, Wu *et al.* 2014), the support vector machine (Zhu and Hu 2013, Zhu *et al.* 2010, Wu *et al.* 2014), the evolutionary neural network (ENN) (Feng and An 2004), the extreme learning machine (Lian *et al.* 2014) and the Gaussian process (Liu *et al.* 2012), etc. In those methods, the grey system method, time series analysis method and ANN method are three main methods. Therefore, the three main methods are analyzed in detail in the follow sections and the new ENN method is proposed to predict the measurement displacement of geotechnical engineering.

2. Introduction of main prediction methods

2.1 Grey system method

Grey system method is a system science method dealing with grey system whose information is known partly, and proposed by Chinese scholar Deng in 1980s'. It has developed quickly and applied extensively in the prediction field (Chen and Huang 2013, Kayacan *et al.* 2010). The most commonly used grey model for prediction is GM(1, 1), which indicates one variable is employed in the model and the first order differential equation is adopted to match the data generated by the accumulated generating operation (AGO). Its main process is as follows.

The original non-negative data series with n entries is

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2),..., x^{(0)}(j),..., x^{(0)}(n)) \tag{1}$$

where, $x^{(0)}(j)$ is the datum at j-th time and n is the total number of data.

The one-time AGO series is

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2),..., x^{(1)}(j),..., x^{(1)}(n)) \tag{2}$$

where, $x^{(1)}(k)$ is the generated datum of $x^{(0)}(k)$ and can be described as

$$x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(j) \tag{3}$$

The Eq. (2) can be described by the solution of one differential equation given as

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{4}$$

where, parameters a and b are the developing coefficient and grey input, respectively.

The parameters a and b can be estimated by least mean squared(LMS) method. If the initial condition is $x^{(1)}(1)$, which is equal to $x^{(0)}(1)$, then the specified solution of Eq. (4) is

$$\hat{x}^{(1)}(k) = (x^{(0)}(1) - \frac{b}{a})e^{-a(k-1)} + \frac{b}{a} \tag{5}$$

where, $\hat{x}^{(1)}(k)$ is the modeled value of $x^{(1)}(k)$.

Substituting k=(n+1) into Eq. (5), the one-step-ahead prediction value can be calculated by

$$\hat{x}^{(1)}(n+1) = (x^{(0)}(1) - \frac{b}{a})e^{-an} + \frac{b}{a} \tag{6}$$

2.2 Time series analysis method

Time series analysis method is a method to study the random sequence that diversifies with time (Box and Jenkins 1989). The construction process of generally used ARMA(p, q) model is briefly introduced as follows.

The nonlinear time sequence is $\{x_t, t=1, 2, \dots, n\}$. In this model, the future value of a variable is assumed to be a linear function of several past observations and random errors. Thus, the underlying process that generate the time series has the form as

$$x_t - \sum_{i=1}^{p} \varphi_i x_{t-i} = a_t - \sum_{j=1}^{q} \theta_j a_{t-j} \qquad a_t \sim \mathrm{NID}(0, \sigma_a^2) \tag{7}$$

where, x_t and a_t are the actual value and random error at time t, respectively. φ_i (i=1, 2, … , p) and θ_j (j=1, 2, … , q) are model parameters. p and q are the orders of the model.

There are two methods to estimate the parameters of p and q. One method is combining the natures of sequence's auto correlation function and partial correlation function with some trials and some judgment laws. Another method is application of ARMA(2n, 2n-1) approximation (Box and Jenkins 1989).

There are two steps to estimate the model parameters of φ and θ. The first step is rough estimation with quadrature method or converse function method. The second step is precise estimation with LMS method based on their rough estimation values.

Generally, it is complicated to predict by time series analysis method. It can be divided into two methods, which are stationary linear variance prediction and new information prediction. For stationary linear variance prediction, the whole previous values are applied, and the principle is that linear prediction variance is minimum. While for new information prediction, the new produced values are applied to predict.

2.3 Artificial neural network method

When the linear restriction of the model form is relaxed, the possible number of nonlinear structures that can be used to describe and predict a time series is enormous. A good nonlinear model should be "general enough to capture some of the nonlinear phenomena in the data". ANN is one of such models that can approximate various nonlinearities in the data (Jacek 1992). It can

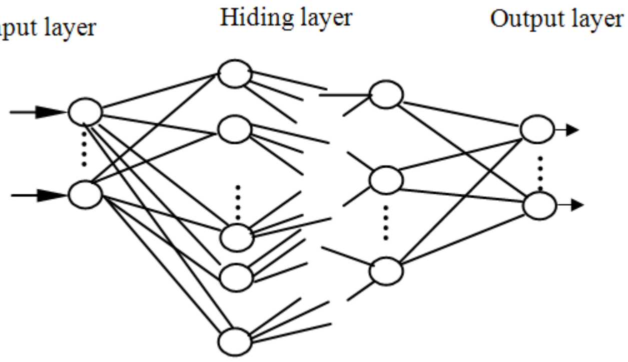

Fig. 1 Basic model of BP network

approximate the complicated time series very well (Luo and Unbehauen 1997).

The generally used ANN model is back propagation (BP) network. There are two processes in the course of this network, which are training course and testing course. The learning algorithm of this network is called error back propagation (BP) algorithm. The basic model of BP network is shown in Fig. 1.

The process of model construction is as follows.

The nonlinear time sequence is $\{x(i), i=1, 2, \dots, n\}$. As for displacement prediction, generally the network structure is multi-input and single-output model. The training sets are created by sample modes from original sequence. If the number of neuron for input layer is p, the number of the training sets will be n-p. The training sets are as follows,

The first sample is,

The input values are $x(1), \dots, x(p)$ and output value is $x(p+1)$;

… …;

The sample which order is t-p is,

The input values are $x(t-p), \dots, x(t-1)$ and output value is $x(t)$;

… …;

The sample which order is n-p is,

The input values are $x(n-p), \dots, x(n-1)$ and output value is $x(n)$.

Training by above samples, the particular network can be obtained.

For a set of input data $x(t)$ and output data $y(t)$, the mapping relation can be gotten using BP network as follows

$$y_k^{t+T} = \sum_{j=1}^{M} f_2[w_{jk} f_1(\sum_{i=1}^{N} w_{ij} x_i^t - \theta_j) - \theta_k] \tag{8}$$

where, x_i^t is the input value of i-th node at time t, w_{ij} is the weight value between the i-th node of input layer and the j-th node of hidden layer, θ_j is threshold value at the j-th node of hidden layer, w_{jk} is the weight value between the j-th node of hidden layer and the k-th node of output layer, θ_k is threshold value at the k-th node of output layer, y_k^{t+T} is the output value at the k-th node at time $t+T$, T is the prediction period, $f_1(\cdot)$ and $f_2(\cdot)$ are activation functions for the nodes of hidden layer and nodes of output layer, respectively.

3. Analysis of main prediction methods

3.1 Grey system method

The construction of grey system model is essentially a curve approximation process. The merit of grey system method is the number of samples that grey system requires is small and its construction process is simple. Moreover, the validity of grey system can be verified. But the grey system has its demerits (Wu *et al.* 1988). The first one is that the time series must be continuous and differentiable. Furthermore, the time series must be expressed by a primary function. The second one is that the grey system can only describe a process, which is monotone increase or decrease.

For the grey system model, the original time series is approximated by the exponential function arbitrarily as its variation rule is unknown and the approximative degree is not illuminated. Moreover, the method to confirm the approximative degree is unknown. Furthermore, the original time series must be conducted by AGO. However, this operation can reduce random error as for certain sequence. While for uncertain sequence, this operation may make the forecasting error larger (Gao and Yin 2011). Therefore, for displacement time series prediction, grey system method must be used cautiously.

3.2 Time series analysis method

This model is essentially a kind of linear autoregression model. It analyzes the statistical law of dynamic data series that diversifies with time. The modality of this model is very simple and this model has good statistical characteristic (Box and Jenkins 1989). But the time series analysis method has its demerits too (Wu *et al.* 1988). The first one is that the time series must be stationary and normal sequence or the sequence must be stationary random time series. The second one is that data of the time series must be expressed by the linear combination of its forepassed data.

Therefore, to apply the time series analysis method well, the data sequence must be stationary, normal and the data can be expressed by the linear combination of its forepassed data.

For geotechnical engineering, the displacement time series generally is not a stationary and normal random series, thus the application of time series analysis model is hard at some extent. Moreover, there generally exists a problem to extract the trend of sequence as to the real displacement time series. But the variation rule of original time series cannot be comprehensively grappled in advance (Gao and Yin 2011). This makes the problem of trend extraction very complicated. In fact, even though the displacement time series has not trend, generally it is not stationary and normal. Moreover, the data of displacement time series cannot be expressed by the linear combination of its forepassed data. Therefore, the above problems restrict the application of the time series analysis method.

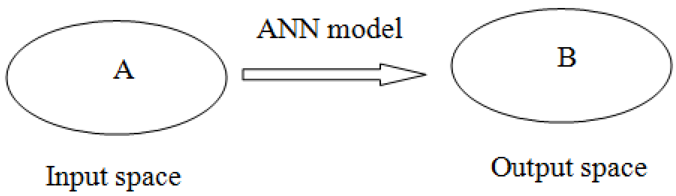

Fig. 2 Mapping of ANN model

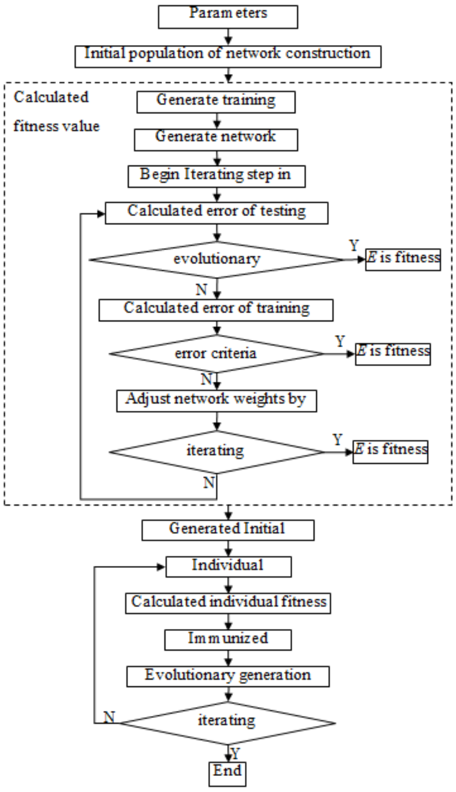

Fig. 3 Flow chart of the evolutionary neural network

3.3 Artificial neural network method

This method is essentially a kind of non-linear autoregression. There is no extra demand for displacement time series by ANN method. Almost any sequence can be analyzed by ANN. For displacement time series prediction, the generally used ANN is BP network, and the prediction method is autoregression. However, there also exist some problems, as follows.

1) Selection of input neuron number

The neuron number of input layer is actually the lingering time step (Gao and Yin 2011). It is a key parameter for sample construction, and generally selected by user's experience or trial and error method. Thus, it is a consuming time work and may not select the suitable neuron number.

2) Selection of hidden layer number and neuron number of hidden layer

The three-layer ANN is generally used for displacement time series prediction (Gao and Yin 2011). This phenomenon has relation with the user's wrong understanding of neural network's mechanism. Many users think the Kolmogorov theorem is the mathematic base of neural network, and in many studies the theorem is depicted as follows (Churing 1995). If the neuron number of hidden layer can be selected randomly and the neuron activation function is sigmoid function, the three-layer network can approximate any continuous function with any precision.

In fact, this understanding about the Kolmogonov theorem is wrong. The previous study (Bao *et al.* 1995) proved that only four-layer ANN can approximate any continuous function with any precision. In addition, for three-layer ANN, the neuron number of hidden layer cannot be selected randomly and it is the term number of the expanding formula of its corresponding function. To remember more samples and approximate a function, the three-layer ANN requires many hidden neurons. Theory and practice all prove that, the robustness of this three-layer ANN is very poor and its computing efficiency decreases very rapidly when number of its hidden neurons increases (Churing 1995). Therefore, to predict the displacement time series, selection the hidden layer number should be an important work.

3) Selection of neuron function

According to the Kolmogorov theorem, using sigmoid activation function, the ANN can approximate any continuous function. Honik (1991) thinks that, the connection between neurons is more important, and the neuron character is non-significant. In fact, this thinking may be wrong. From the point of mathematical mapping, the hidden neuron activation function affected the network character very strongly. Based on the mathematical theories, for approximation of a function, the different neuron activation function corresponds to different radix function. Thus, the generalization of neural network will be different largely.

4) Extrapolation of neural network

Substantially, the displacement time series prediction is the application of extrapolation for ANN. From the solution space theory of neural network (Jacek 1992), an ANN expresses one of particular mapping, and the scope of original shape space confines the solution space of ANN, that is to see, the mapping scope of ANN is determined completely by the training samples, shown in Fig. 2.

However, the ANN has character of extrapolation at some extent through some pretreatment of training samples (Jacek 1992). Thus, it is a key work to improve the extrapolation of ANN for the displacement time series prediction.

From above analysis, there are no more requirements for the displacement time series in ANN method, thus, ANN method is one good method to predict the displacement time series in geotechnical engineering. However, this universality makes the construction of ANN model difficult, and there also exist some problems for the application of ANN method (Gao and Yin 2011). Thus, generally, it is very necessary to have some experience when using ANN method for the displacement time series prediction.

4. New prediction method-evolutionary neural network

To solve the main problems of ANN method for the displacement time series prediction, one new ENN has been proposed in this study. In this ENN, the main parameters of ANN are selected by immunized evolutionary programming (IEP) (Gao 2004), and the weights are confirmed by the modified back propagation (MBP) algorithm.

In this ENN, the utilized neuron activation function is

$$f(s)=\frac{1}{1+e^{(-us)}} \tag{9}$$

where, u is the parameter of neuron activation function.

Therefore, the main parameters to be selected by IEP include the number of input neurons, the number of hidden layer, the number of hidden layer neurons, the parameter of neuron activation function and two parameters of MBP algorithm (the iterating step and the inertia parameter).

However, to study conveniently and directly, the indirect coding method is used. Additionally, to make the model as simple as possible, the full-linking network is applied. The designed ENN must satisfy the follow conditions:

a. the input neuron has no input linking,

b. the output neuron has no output linking,

c. there is only one linking between any two neurons, and

d. there is only feed forward linking between any two neurons.

The details of the ENN are as follows.

1) The search ranges of parameters are initially provided. The evolutionary parameters are specified to include the evolutionary generation stop criteria, the individual number in one population, the error criteria of the evolutionary algorithm, the number of output neurons in the neural network, the iterating stop criteria and the iterating error criteria in the MBP algorithm.

It must be noted that, to construct the suitable samples, the number of input neurons must be smaller than the total number of the displacement time series.

2) One network construction is generated by some random numbers, which are the number of input neurons, the number of hidden layer, the number of hidden layer neurons and the parameter of neuron function. One type of MBP algorithm is also created by two random numbers, namely the iterating step and the inertia parameter. One type of neuron activation function is also created by the random value of the parameter of neuron activation function. Using these inputs, one individual (one ANN) can be generated by these parameters.

It must be noted that, because some parameters, which are the number of input neurons, the number of hidden layer and the number of hidden layer neurons, are integer numbers and some parameters, which are the parameter of neuron function, the iterating step and the inertia parameter, are real numbers, the expressions of one individual must be structural data; the corresponding pseudocode is as follows.

```
Type  individual
Integer  input-neuron-number
Integer  hidden-layer-number
Integer  hidden-neuron-number
Real    p-fun
Real    W[i][j]
End  type  individual
```

where, $W[i][j]$ is the matrix of link weights. There are three matrices: the matrix of link weights between the input layer and the hidden layer, the matrix of link weights between the hidden layers and the matrix of link weights between the hidden layer and the output layer. The parameters *input-neuron-number*, *hidden-layer-number* and *hidden-neuron-number* are the number of input neurons, the number of hidden layer and the number of hidden layer neurons. The parameter *p-fun* is the parameter of neuron activation function.

3) For one individual, these steps can be used to obtain its fitness value.

a. The learning samples for the neural network are constructed from the displacement time sequence, based on number of input neurons. The number of samples is noted.

b. The entire learning sample group is divided into two groups. One group contains the training samples used to create the non-linear mapping network. The other group includes the testing samples used to test the generalization of the network.

c. The initial linking weights of the network individuals are randomly generated.

d. The iteration of the MBP algorithm begins.

e. The selected network individual is trained by testing samples; the square error E is computed, and this error is used as the minimum error for the entire training, as min$E$=E. If min$E$ is smaller than the error criteria of IEP, the fitness value is min$E$; the computing process continues to step 3.

f. The selected network individual is trained by the training samples. If its training error is less than the iterating error criteria of the MBP algorithm, the fitness value is min$E$; the computing process continues to step 3.

g. The whole linking weights are adjusted by the MBP algorithm.

h. The iteration of the MBP algorithm continues and the computing process returns to step *e*.

i. If the iteration number of MBP algorithm is larger than the iterating stop criteria of MBP algorithm, the fitness value is min$E$. The computing process returns to step 3.

4) If the evolutionary generation reaches its stop criteria or the computing error reaches the error criteria of the IEP, the algorithm stops. At this time, the best individual in last generation is the searched result.

5) Every individual in the population is mutated. There are different data types for each individual and the varying mutation types are used for each parameter. For the values of the integer numbers, the uniform mutation is used. For parameters of real number, the adaptive Cauchy mutation is applied and the offspring population is generated.

6) The fitness value of each individual in the offspring population is calculated by the method shown in step 3.

7) The sets of offspring population and parent population are selected and then the new offspring population is generated.

8) The number of the evolutionary generation increases by 1, and the computing process advances to step 4.

The flow chart of the ENN for displacement prediction is shown in Fig. 3.

The parameters used in the above algorithm can be confirmed. Therefore, the suitable ANN for displacement prediction can be obtained. Because the fitness value is the testing error, the capacities of the approximation and the generalization for the ANN model should be acceptable.

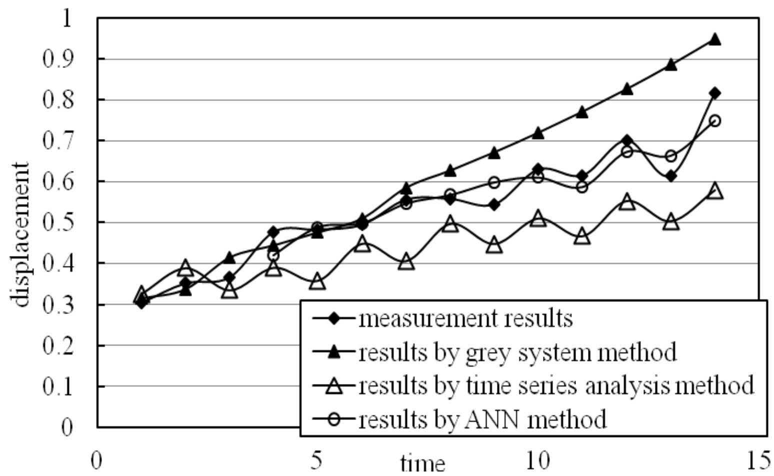

Fig. 4 Comparison study of grey system, time series analysis and ANN methods for one tunnel of Geheyan water power station

Table 1 Computing accuracy of grey system, time series analysis and ANN methods

Methods	Grey system method	Time series analysis method	ANN method
Correlation coefficient	0.909	0.890	0.928

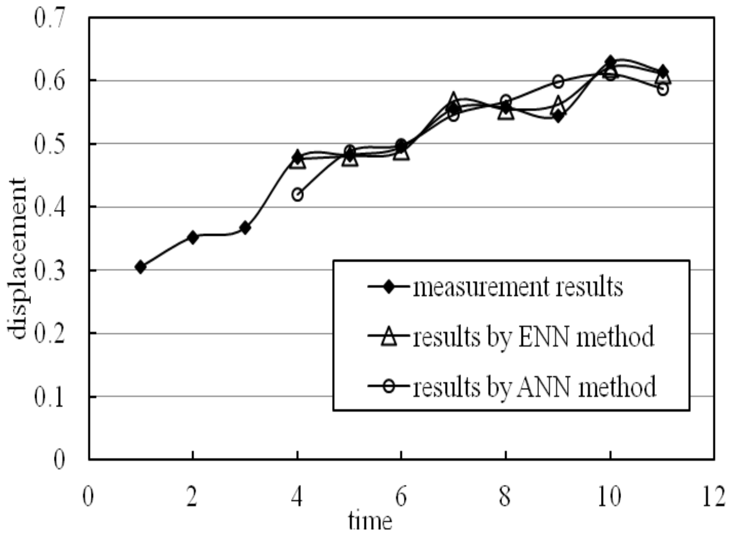

Fig. 5 Computational results by ANN and ENN methods for one tunnel of Geheyan water power station

Table 2 Computing accuracy of ANN and ENN methods

Methods	ANN method	ENN method
Correlation coefficient	0.869	0.987

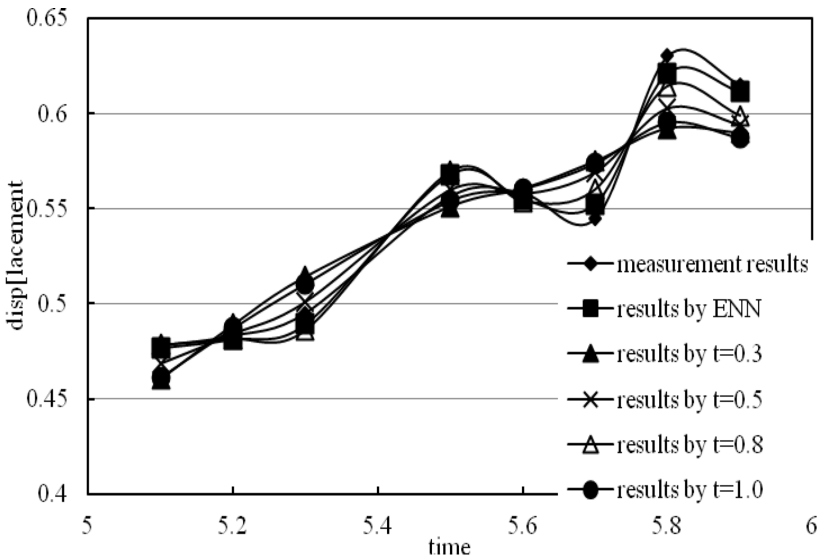

Fig. 6 Computational results with different neuron activation functions of ANN method for one tunnel of Geheyan water power station

Table 3 Computing accuracy of ENN and ANN methods with different neuron activation functions

Methods	ENN method (t=0.69)	ANN with t=0.3	ANN with t=0.5	ANN with t=0.8	ANN with t=1.0
Correlation coefficient	0.993	0.922	0.962	0.979	0.930

5. Case studies

5.1 Displacement prediction for one underground engineering

To verify the analysis results in this study, the measurement displacements of one tunnel for Geheyan water power station in China are applied.

Geheyan water power station is one main cascade hydroelectric station located on the Qingjiang river which is a tributary of the Yangtze River (the largest river of China). Its diversion tunnel is located at the left bank, whose length is 624 m. To monitor its stability, there are some displacement measurement sections in this tunnel. In this study, the measurement results of one main section are used. For this section, the long time displacement measurement for about two months have been conducted. Thus, almost twenty sets of data for displacement measurement have been obtained. In this study, fourteen sets of data removed the abnormal ones are used.

Firstly, the comparison study of grey system method, time series analysis method and ANN method is conducted. The results are shown in Fig. 4. In this study, the grey system method is GM(1,1) model, and the time series analysis method is ARMA(2, 1) model. The ANN method is BP network, whose structure is 3-17-1.

From Fig. 4, the result of the grey system method is nearly one monotonous increase curve. Thus, it cannot reveal the fluctuating law of the real measurement results. While, the result of the time series analysis method is nearly one wavy line, and it cannot reveal the increase law of the real measurement results. Therefore, the prediction errors of those methods are all large. However, the result of the ANN method is agreement with the measurement displacement well, and it can describe the change rule of measurement displacement well. Furthermore, the prediction error of the ANN method is the least. Thus, the results of the application for this real tunnel have verified the analysis results in section 3.

Moreover, to compare the computing accuracy of those three methods, the quantitative criteria of the correlation coefficient is applied. The criteria for three methods are summarized in Table 1.

From Table 1, the correlation coefficient of the ANN method is 0.928, which is the largest. Thus, the ANN method is the best method to predict the displacement for geotechnical engineering. However, the prediction result of grey system method is better than that of time series analysis method because the displacement time series for this tunnel has obvious increasing trend. Therefore, the comparison results can be used to verify the analysis results in section 3 too.

Secondly, to verify the computational performance of new ENN method, the ANN and ENN methods are all used to predict the displacement time series. In this study, to reveal the difference between ANN method and ENN method more obviously, one part of the measurement displacement time series, which has 11 values, is applied. This part of the measurement displacement time series is the former 11 data of the original data series. In this study, the former 10 values are used to construct the ENN model, and the last one is used to test the ENN model. The computational results of two methods are shown in Fig. 5.

The computational results for the parameters of ENN are follows. The optimal structure of

ANN is 3-3-8-1. The iterating step and the inertia parameter for MBP algorithm are 0.55 and 0.8, respectively. The parameter of neuron activation function is 0.69.

As shown in Fig. 5, the computation results of new ENN method are much better than those of ANN method. Not only its approaching performance is good, but also its prediction generalization ability is good too.

Moreover, to verify the good performance of new ENN method more detailed, the comparison study between the ANN and ENN methods based on their computing accuracy has been conducted using the quantitative criteria of the correlation coefficient. The results are summarized in Table 2.

From Table 2, the correlation coefficient for ENN method is 0.987, which is larger than that for ANN method (0.869). Therefore, the prediction results of new ENN method is better than that of ANN method. And the new ENN method is an acceptable method to predict the displacement of geotechnical engineering.

Finally, because the effect of the parameter of neuron activation function is studied little in previous studies, its effect is analyzed in this study. To study the effect of the neuron activation function, the parameter of neuron activation function is taken as 0.3, 0.5, 0.8 and 1.0. At the same time, the other parameters are the same as those of above ENN model. The computational results are as shown in Fig. 6. In this study, to compare clearly, only one part of the measurement displacement time series is applied. This part is the middle 8 data of the original data series, whose change is relatively stable.

From Fig. 6, the different neuron activation function can obtain the different computation results. Thus, the effect of neuron activation function on the prediction results is very large. However, the four results with different parameter of neuron activation function, which are 0.3, 0.5, 0.8 and 1.0, are all poorer than that of ENN method. The research results can not only verify the analysis results in section 3, but also verify the application results of the ENN for underground engineering.

Moreover, to analyze the effect of the neuron activation function more detailed, based on the quantitative criteria of the correlation coefficient, the computing accuracy of ENN and ANN methods with different neuron activation functions are compared. The results are summarized in Table 3.

From Table 3, the computing results for ENN and ANN method with different neuron activation functions are different. And the result by ENN method is the best. Therefore, the effect of neuron activation function on the prediction results is serious. Moreover, the analysis results in section 3 are verified too.

5.2 Displacement prediction for one rock engieering

To verify the analysis results in this study, the measurement displacements of the middle isolated pier of ship lock in the Three Gorges Project, China are applied.

The Three Gorges Project is the largest water conservancy and the largest hydropower engineering in China, even in the world. In order to meet the requirements of the large navigation, the displacement of the middle isolated pier of ship lock must be controlled very strictly. Therefore, the longtime displacement measurement for the middle isolated pier of ship lock has been performed for about two years. The measurement displacements are as shown in Fig. 7.

In this study, based on above analysis, the grey system method, ANN method and ENN method are all applied for comparison. To verify the generalization prediction performance of the three methods for displacement prediction, the displacements before June of 1999 are used in the model process, and the last displacement is used to verify the prediction performance of model. The results are as shown in Fig. 7.

The computational results for the parameters of ENN are follows. The optimal structure of ANN is 12-9-5-1. The iterating step and the inertia parameter for MBP algorithm are 0.37 and 0.92, respectively. The parameter of neuron activation function is 0.71.

Based on the quantitative criteria of the correlation coefficient, the computing accuracy of the grey system method, ANN method and ENN method are compared, as shown in Table 4.

As shown in Fig. 7 and Table 4, the result of grey system method can only describe the variation trend of the displacement sequence, and is not agreement with the real displacement sequence well. Moreover, its computing accuracy is the poorest. The results of ANN and ENN methods are all agreement with the real displacement sequence well, and their computing accuracy are almost similar. However, the computing results of new ENN method are closer to the real displacement sequence than those of ANN. And, the computing accuracy of ENN method is better than that of ANN method. Especially, when the measurement displacement changes largely, the result of new ENN is more superior to that of ANN. However, the approximation sequence and the generalization prediction sequence are all coincided with the measurement displacement sequence very well. And the prediction precision is very high. Therefore, the new ENN method is a good method to predict the measurement displacements for the middle isolated pier of ship lock in the Three Gorges Project.

Thus, the application results of displacements prediction for the middle isolated pier of ship lock in the Three Gorges Project have also verified the analysis results of the section 3 and the good performance of the new ENN method.

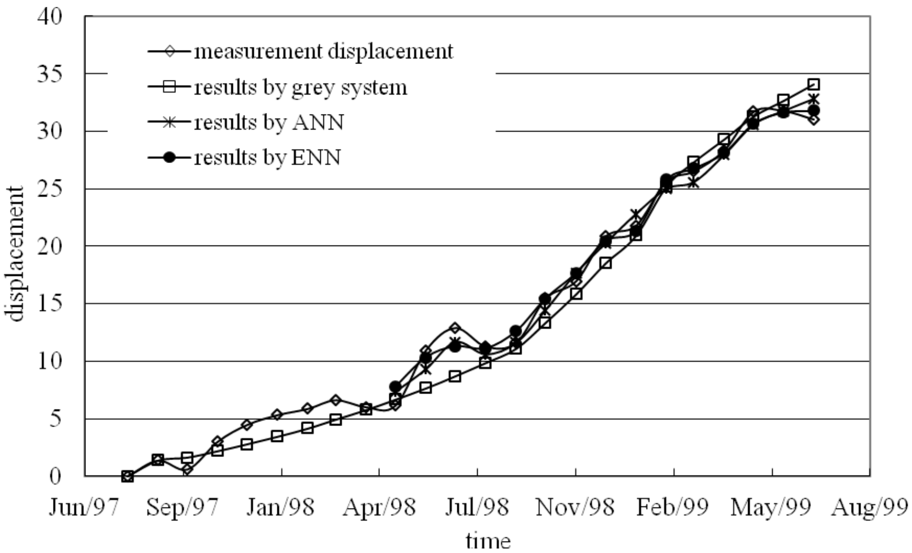

Fig. 7 Computational results for middle isolated pier of ship lock in the Three Gorges Project

Table 4 Computing accuracy of grey system, time series analysis and ANN methods

Methods	Grey system method	ANN method	ENN method
Correlation coefficient	0.988	0.993	0.996

6. Conclusions

It is very important to predict the displacement of the geotechnical engineering. Therefore, many methods have been proposed to conduct this problem. The grey system method, time series analysis method and ANN method are three main methods. Based on the brief introduction, their merits and demerits all have been analyzed. Moreover, to overcome the main shortcomings of the ANN method, one new ENN method is proposed to predict the measurement displacement of geotechnical engineering. Finally, through two real engineering practice, the analysis results have been verified. According to the studies, the follow conclusions can be drawn,

- The three methods, namely grey system method, time series analysis method and ANN method, are all approximation methods to displacement sequence, and have their own ranges of application.
- Essentially, grey system method is a kind of exponential approximation to displacement sequence, and time series analysis is linear autoregression approximation, while ANN is nonlinear autoregression approximation. Thus, the ANN method is the best one.
- The prediction results of new ENN method is very high, and its approximation sequence and the generalization prediction sequence are all coincided with the measurement displacement sequence very well. Moreover, its computing accuracy is better than that of ANN method. Thus, the new ENN method is a good method to predict the measurement displacements of geotechnical engineering.

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