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An optimized neural network with a hybrid GA-ResNN training algorithm: applications in foundation pit

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Abstract
The prediction of foundation pit deformation is of great significance in ensuring the safety of neighbors and efficiency of construction. The back-propagation neural network (BPNN) is one of the most successful models that have been implemented for data prediction. An accurate mapping relationship cannot be constructed by directly applying neural networks due to the measured data of foundation pit suffer from small quantity and big noise. In the present study, the main idea of residual network (ResNet) was introduced in prediction, and genetic algorithm (GA) and back propagation (BP) were coupled to develop a hybrid GA-ResNN training algorithm with global search capabilities. The dimension of the input data is doubled by overlapping and encoding the input data. The dependence of the neural network on the initial model can be reduced using GA and ResNet. Cases reported in the literature are used to demonstrate the effectiveness and accuracy of the proposed model.

Keywords Foundation pit · Genetic algorithm · BP neural network · Residual training · GA-ResNN model

Introduction

With the rapid development of urban construction, the number and scale of underground projects have risen sharply, along with the number of accidents in deep foundation pit. A series of problems such as damage to foundation pits, casualties, economic losses, damage to surrounding buildings, and even collapse also occur frequently. Unpredictable effects and losses on society were caused due to those problems. Therefore, the prediction work during the construction of deep foundation pits is of great significance in ensuring the safety of neighbors and efficiency of construction. Deformation prediction work of foundation pit projects consists of a lot of contents, and monitoring works, e.g., surrounding ground surface settlement, surrounding pipeline displacement, deformation of enclosure structure, and bottom heave, should be carried out in practice. Mathematical models for deformation prediction of deep foundation pits established by traditional theory have a disadvantage of low accuracy, which are difficult to meet the requirements of prediction accuracy of deep foundation pit projects.

Currently, there are many methods for processing and predicting the deformation data in geosciences including the application in foundation pit. Time series (Shen et al. 2013), gray system (Guo et al. 2015), regression statistical analysis (Arthur et al. 2015), Kalman filtering model (Boukharouba 2013), back propagation neural network (BPNN) (Lv et al. 2020), artificial neural network (ANN) (Riahi-Madvar and Seifi 2018; Riahi-Madvar et al. 2021a; Ghorbani et al. 2020, 2021), and adaptive network-based fuzzy inference system (ANFIS) (Riahi-Madvar et al. 2021b; Li and Cheng 2021) were used for most cases to date. Among the various neural network models used for predicting the deformation in foundation pits, the BPNN has the ability to map complex nonlinear problems and unknown relationships in a simple structure, also with a good nonlinear fitting ability and self-learning ability (Wang et al 2015). The weights and bias of BPNN are calculated by gradient descent based on a local search algorithm. BPNN has been widely used in practice, although drawbacks including slow convergence speed and the

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appearance of local extremum still exist (French et al 1992). Drawbacks came from the synaptic weights and errors generated randomly before the training of neural network. With each repeated operation of the training of neural network training, the final weight of each time was evaluated by BPNN algorithm, in which the trained neural network has different prediction performance and convergence speed.

It is necessary to propose a method to improve the performance and global convergence of BPNN to minimize the inconsistency. Some nature-inspired algorithms that find the global optimum have been developed to hybridize with artificial intelligence models and improve the performance of these models (Niu et al. 2018). For example, Cui et al. (2021) applied PSO optimization algorithm to optimize and improve the GM (1, 1) model and the BP network model, and Madvar et al. (2020) proposed a hybridized ANN With PSO and cat swarm optimization (CSO) algorithms. Genetic algorithm (GA), i.e., a global searching technology with gradient-free method inspired by evolutionary processes, or residual network, i.e., a framework that reformulates the layers as learning residual functions with reference to the layers input, instead of learning unreferenced functions, can be used to improve the network structure of BPNN. Asadi et al. (2013) proposed a hybrid intelligent model for runoff prediction by combining genetic algorithms and feed forward neural networks. Irani and Nasimi (2011) utilized a hybrid genetic algorithm–neural network strategy to predict permeability of Mansuri Bangestan reservoir. Khandelwal and Armaghani (2016) proposed a hybrid genetic algorithm (GA)–artificial neural network to estimate convenient drilling rate index (DRI). He et al. (2016) proposed the deep residual learning for image recognition and won 1st place on the tasks of ImageNet detection. Zhang et al. (2017) used residual learning in denoising convolutional neural networks (DnCNNs) to embrace the progress in very deep architecture, learning algorithm, and regularization method into image denoising.

However, there is no hybrid method that combined GA and residual network in predicting the deformation of deep foundation pits. To get an optimized neural network with a hybrid GA-ResNN training algorithm for predicting deformation of the foundation pit, a hybrid model using GA optimized residual neural network was established in this work. To demonstrate the effectiveness and accuracy of the proposed model, cases reported in the literature are used in this paper. The present work can provide accurate guidance and suggestions for the construction of the foundation pit.

A hybrid GA-Res neural network

Introduction of residual network (ResNet)

The concept of residual network was first proposed by He et al. (2016) and the training results of ResNet won 1st

place on the ILSVRC 2015 classification task. The residual network can solve the problems of gradient dispersion and gradient explosion caused by the increase in the number of network layers. Assuming that the latter layers of the deep network are identity mapping, the model degenerates into a shallow network. It is more difficult to directly fit some layers to a potential identity mapping function $A(x) = x$. However, if the network is designed as $A(x) = F(x) + x$, as shown in Fig. 1, the idea of a residual network is to transform the whole process into learning a residual function $F(x) = A(x) - x$. Therefore, identity mapping is built $A(x) = x$ when $F(x) = 0$.

Introduction of GA-BP algorithm

The back-propagation (BP) algorithm is one of the most successful methods that have been implemented for network optimization, which was proposed by a group of scientists led by Rumelhart et al. (1986). A BP neural network (BPNN) model is composed of layers (input, hidden, and output layers), neurons, and weights between neurons. Genetic algorithm (GA) is a computational model that simulates the natural evolution of Darwin's theory of evolution and the biological mechanism of genetics. The theory and method of GA was first proposed by Holland (1975). Individuals with better fitness will be reserved via the processes including training, optimizing the initial population, and selecting, crossing, and mutating genetic genes.

Figure 2 shows the flowchart of the GA optimized BPNN model, which can be divided into three parts: determination of BPNN structure, optimization process
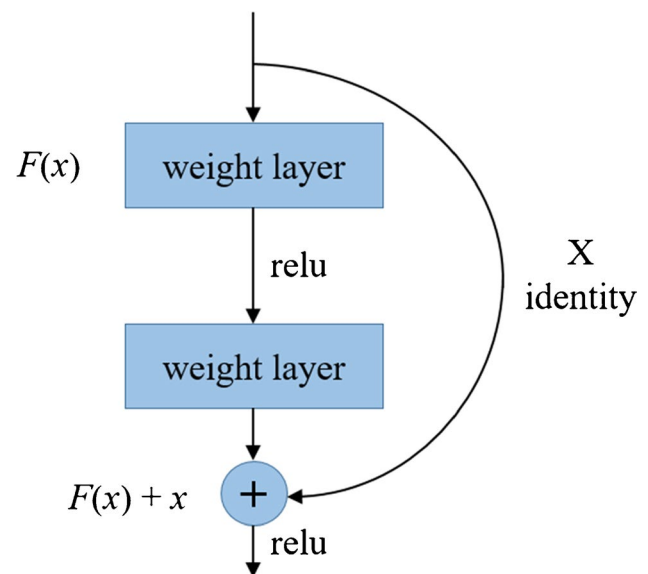

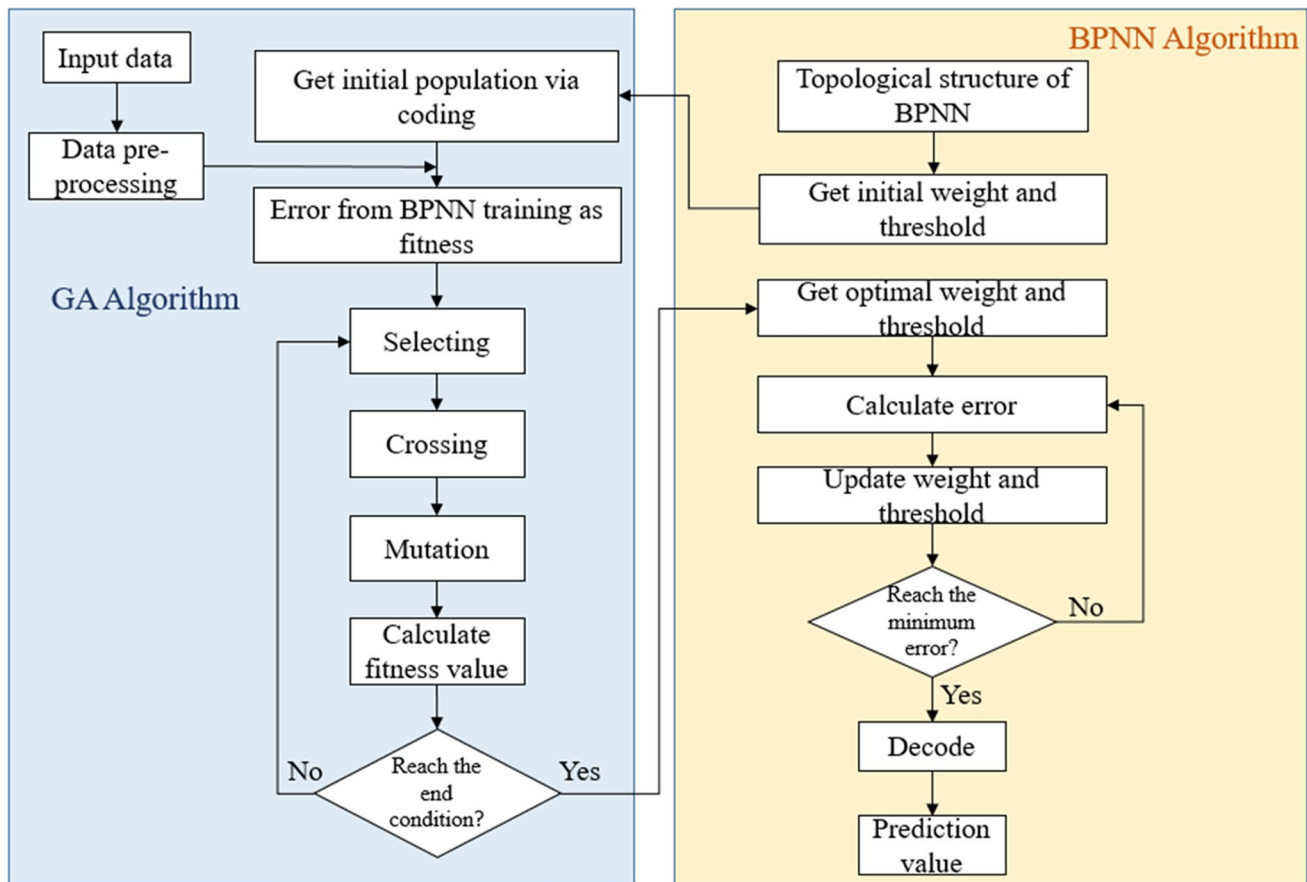**Fig. 1** Flowchart of residual learning (He et al. 2016)

Fig. 2 Flowchart of GA-ResNN model

of GA, and prediction of BPNN. Better initial weights and thresholds of network can be acquired via the GA-ResNN. The basic idea is to use individuals as the initial weights and thresholds of the network and the prediction errors of the BPNN as the fitness value. Finding the optimal individual through selecting, crossing, and mutation, which is also the process to find the optimal initial weight and threshold.

The optimal initial weight and threshold are substituted into the BPNN network for training; the calculation is not terminated until the global error is less than the limited error. BPNN can converge quickly to avoid falling into a local minimum, and integrates the optimization of the GA; in addition, the calculation speed and accuracy of the BPNN can be improved.

Introduction of A hybrid GA-Res neural network

This paper combines the idea of residual training and GA-BP algorithm and proposes a hybrid GA-ResNN model. Data residuals are fitted by GA-BP algorithm to achieve the expected results. The implementation process will be described in the following section.

Deformation predicting model of foundation pit

Training samples for foundation pit data

The primary task for building a prediction model of neural network on foundation pit deformation is to reasonably select training samples. Training samples need to be selected according to their different characteristics as follows:

(1) Small amount of data. Model suffers from some inaccuracies in prediction results if the number of training samples is not enough. Therefore, data grouping is used in this prediction model to reasonably expand the amount of data on the original basis. Taking three pieces of data as a group, and comparing the prediction result with the fourth data, the error is used as the fitness value and then the GA algorithm is performed in the flowchart, as shown in Fig. 3.

(2) Diversified type of data. Level indicators include self-parameters (SP), supporting structure (SS), excavation scheme (ES), dewatering (DW), safety monitoring (SM), peripheral influence (PI), structure status of the

Fig. 3 Data grouping of the training samples
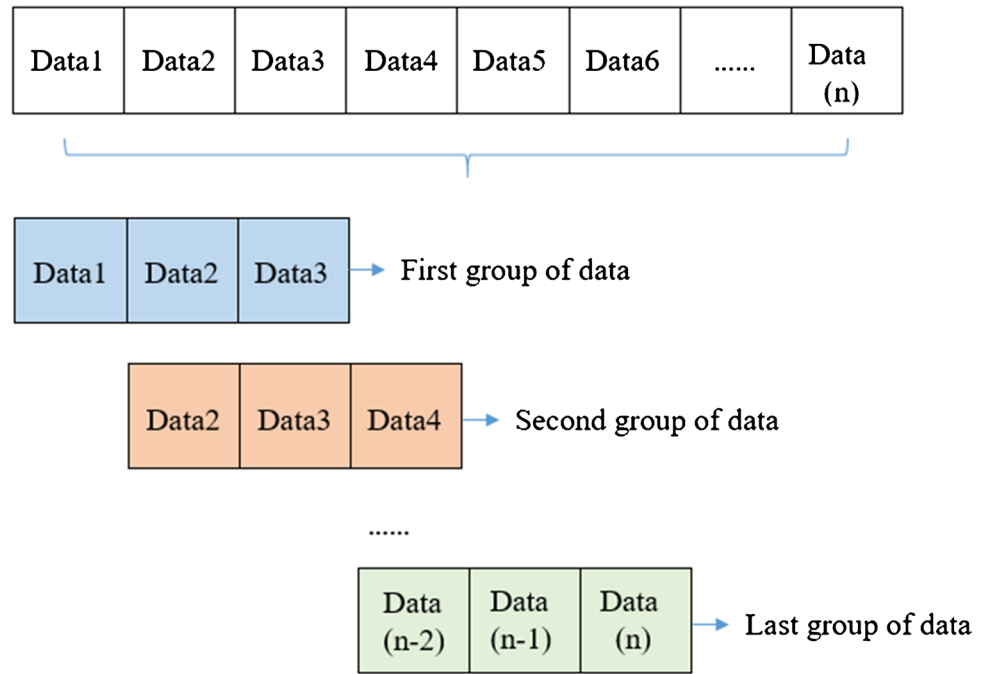
existing tunnels (SET), and deformation monitoring of tunnels in construction period (DMT). The ability to reveal the characteristics of the deformation of foundation pit is not only to rely on the factors that have obvious effect to the results, which means only selecting a part of factors as the model input is not sufficient.

Therefore, the prediction model in this paper can realize the function of predicting any secondary indicators. After selecting the level indicator, then select the desired secondary indicator you want for the prediction result. The classified indicators that affecting the deformation of the foundation pit are shown in Table 1. In the process of data screening, indicators that have no reference value have been removed because of the reason that data has not changed over time.

(3) Data is suitable for model training and predicting. The deformation of the foundation pit has the characteristics of trending, randomness, and volatility, which is suitable for training and predicting of the model. Meanwhile, boundedness brought by a certain regression model in the analysis of time series can be overcome by GA optimized BPNN algorithm.

(4) Multiple data training and predicting methods. Data training and predicting methods include the following three methods: single indicator using data under the same level of indicator, single indicator using all data from all level indicators, single indicator using its own data only.

The calculation speed of the second method is the lowest among the three methods because it gets all the data involved in, and the correlation of indicators under different types of level indicator is not as strong as that of under the same indicator. The third method adopts data under the same single indicator for training and predicting; drawbacks such as low efficiency and inaccurate results appear when the data has a low number in amount under nonlinear fitting. Therefore, the first method is used in this paper.

Model implementation

To train the proposed GA-ResNN model, the GA-ResNN method was programmed using the MATLAB software (see the main coding structure shown in Fig. 4). The optimization residual of BPNN is taken as the initial value of GA, and the expected results will be output after the operations of selecting, crossing, mutation, and calculating the fitness.

Rationality verification of GA-ResNN method

Introduction of engineering case

A square foundation pit in Xi'an is taken as the example as well as the measured data (Zhang 2017). Foundation pit was located on the east side of a high-speed railway station and on the south side of the coach station. The national highway passes from the west side of the square. The main

function of the project was an underground garage and an underground shopping mall. The north and south parts were symmetrically arranged on both sides of the subway shield section, and the two sections were connected by three connecting channels at the upper part of the shield section.

There are mainly two parts of risk influential factors for the construction of deep foundation pit near an existing tunnel, e.g., one is the condition of the existing tunnel, and the second part is the scale, stability, and impact on the surrounding environment of the deep foundation pit. According to the analysis of Zhang (2017), deformation and failure form of deep foundation pit, deformation form of existing tunnel, and the safety level analysis of deep foundation pit based on gray correlation degree, the influencing parameters of deep foundation pit during the construction are summarized in Table 1.

Table 1 Indicators affecting the deformation of foundation pit

Level indicators	Secondary indicators
Self-parameters (SP)	Soil strength of foundation pit
	Excavation depth of foundation pit
	Length to width ratio of foundation pit
Supporting structure (SS)	Single excavation depth of diaphragm wall
	Single excavation length of diaphragm wall
	Single excavation thickness of diaphragm wall
	Insertion depth of supporting pile (wall)
	Deformation modulus of soil in reinforced area
	Tension of anchor cable
	Strut axial forces of steel
Excavation scheme (ES)	Single excavation depth
	Single excavation area
	Load near foundation pit
	Exposure duration at bottom of foundation pit
Dewatering (DW)	Groundwater level
	Change rate of groundwater level
Safety monitoring (SM)	Accumulated horizontal displacement of supporting pile
	Horizontal displacement rate of supporting pile
	Accumulated vertical displacement of supporting pile
	Vertical displacement rate of supporting pile
	Accumulated horizontal displacement of diaphragm wall
	Horizontal displacement rate of diaphragm wall
	Accumulated bottom heave
	Change rate of bottom heave
	Groundwater level
	Change rate of groundwater level
	Accumulated ground settlement
	Change rate of ground settlement
Peripheral influence (PI)	Horizontal distance between foundation pit and existing tunnel
	Vertical distance between foundation pit and existing tunnel
Structure status of the existing tunnels (SET)	Structural strength of existing tunnel
	Crack width of existing tunnel
	Buried depth of existing tunnel
Deformation monitoring of tunnels in construction period (DMT)	Accumulated horizontal displacement of tunnel structure
	Horizontal displacement rate of tunnel structure
	Accumulated vertical displacement of tunnel structure
	Vertical displacement rate of tunnel structure
	Convergence of tunnel section
	Convergence rate of tunnel section

Fig. 4 Code structure of GA-ResNN algorithm

GA-ResNN Algorithm
1. Solution optimized by BPNN is set as initial solution of GA
2. Initialize the GA parameters: Population size N, Evolution in Time T, Crossing Probability Pc, Mutation probability Pm
3. Initialize p(t)
4. %p (t) represents the t generation population, including w and b in BPNN
5. Calculating fitness F
6. **While** F>F$_{min}$
7.   **For** t=1:T
8.   Pairs of individuals in a population p(t)
9.   **if** (random (0 ,1) < Pc)
10.   Perform crossing operations
11.   **End**
12.   **if** (random (0 ,1) < Pm)
13.   Perform mutation operations
14.   **End**
15.   Get new population p(t+1)
16.   Calculating fitness F
17.   **End**
18. **End**

Design of topological structure in GA-ResNN

Number of input layer

Number of input layer is the types of data times the number of data which can be realized by the following code (Rumelhart et al. 1986), e.g., inputnum=m*num_g.

Number of hidden layer

The number of hidden layers is generally determined by empirical formula. Researchers have accumulated a lot of experiences for choosing the number of hidden layer during a long time using the BPNN model. The specific formula can be expressed as follows (Zhang 2017):

$$w = \sqrt{m + n + a} \qquad (1)$$

where m is the node number of input layer, n is the node number of output layer, w is the node number of hidden layer, and a is usually taken in [1, 10] and is determined as 1 after several times of calculation in this paper.

Number of output layer

There is only one node in output layer which means the results only related to one indicator for each time of the calculation.

The topological structure of GA-ResNN is shown in Fig. 5. Users can input any one of the desired indicators within the edited range (self-parameters (SP), supporting structure (SS), excavation scheme (ES), dewatering (DW), safety monitoring (SM), peripheral influence (PI), structure status of the existing tunnels (SET), deformation monitoring of tunnels in construction period (DMT)) in the input layer according to their own needs. After the calculation of GA-ResNN, the prediction results of the desired indicator will be output. Taking the example of soil strength of foundation pit (see Table 1). Soil strength of foundation pit is one of the secondary indicators of self-parameters (SP), so the procedure is calling for the SP model first, and data of soil strength of foundation pit in known time-series as input variables, then the output result will be the same variables but in the future time-series, which is the next two days in our case.

Training samples

There are 39 secondary indicators in measured data, 5 of which remain the same during the measured period. The remaining data from 34 secondary indicators are used in this paper, and each indicator has 14 sets of measured data in 14 days. The construction of training samples refers to the content involved in "Training samples for foundation pit data." See the appendix for all measured data used in this paper.

Parameters setting of GA

The optimal initial weight for BPNN is determined by GA without making any change on the topological structure of neural network while the GA-ResNN prediction model is under working. The GA method can better prevent the neural network from falling into local extremes and improve the training speed. The number of iterations
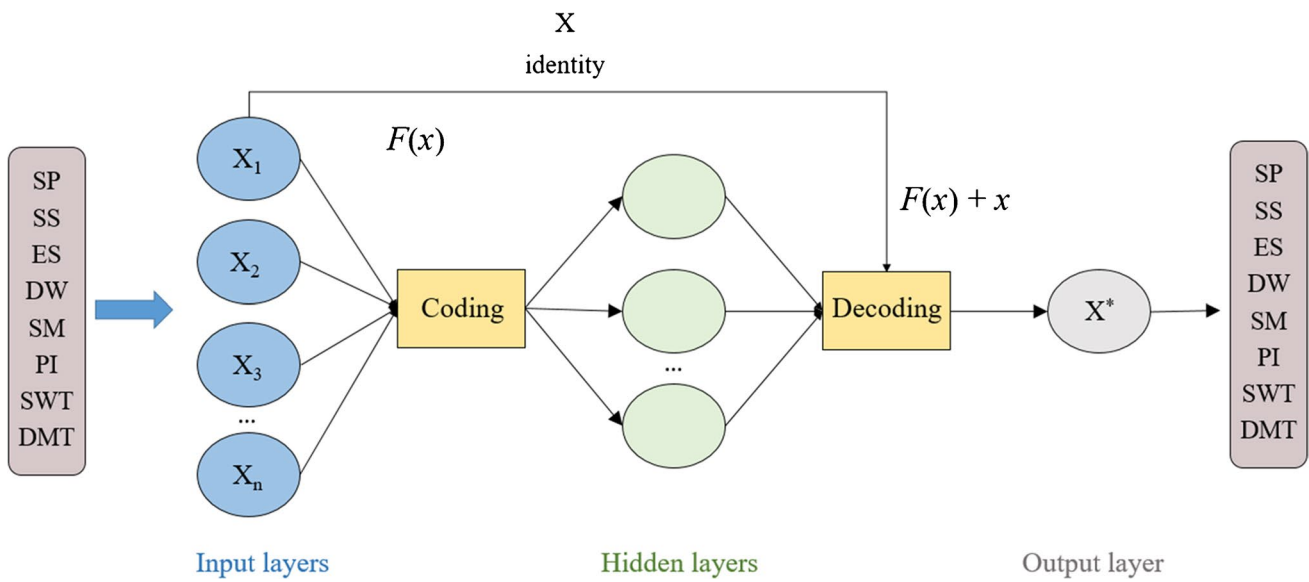
Fig. 5 Topological structure of GA-ResNN

of the genetic algorithm is controlled by a specified maximum number of iterations. In this paper, the parameters of GA algorithm are already fine-tuned based on the research of Li (2007), the maximum iteration of each optimization process is set as 50, the population size is 30, the cross selection probability is 0.3, and the mutation probability is 0.2.

Results on GA-ResNN prediction model

The total number of data is 34 sets due to that there are 34 secondary indicators in total. Only 30 sets of data are randomly selected for analysis and testing to display the results clearly. Each 10 sets of data is grouped for the same reason of displaying clearly. Due to our model is

a time-series regression model with the same input and output variables, the data of secondary indicators are the variables in our model. Data of the known time series are used for model training, so the prediction results of the next two days can be realized for output. Therefore, the results from the two days will be separately analyzed.

Tables 2, 3, 4, 5, 6, and 7 show the measured data, the predicted value of BPNN, the predicted value of GA-ResNN, and the errors E between them, separately. Tables 2 and 3 show the first 10 sets of data in the next two days separately, Tables 4 and 5 show the second 10 sets of data in the next two days separately, and Tables 6 and 7 show the last 10 sets of data in the next two days separately. The calculation formula of E can be expressed as:

Table 2 Errors on predicted value and group A of measured value

Indicators (unit)	Measured value $R1$	Predicted value on BPNN P_b1	Predicted value on GA-ResNN P_a1	$E1$ (%)
Soil strength of foundation pit (MPa)	0.27	0.32	0.31	3.46%
Tension of anchor cable (kN)	286.1	284.04	286.47	0.59%
Strut axial forces of steel (kN)	168.3	155.86	167.71	7.05%
Load near foundation pit (kPa)	218	215.06	217.55	1.14%
Groundwater level (m)	62.9	63.55	62.94	0.96%
Accumulated horizontal displacement of supporting pile (mm)	7.56	7.25	7.54	3.83%
Accumulated bottom heave (mm)	4.9	4.36	4.50	2.85%
Buried depth of existing tunnel (m)	9.8	9.29	9.62	3.38%
Vertical distance between foundation pit and existing tunnel (m)	3.9	3.82	3.99	−0.38%
Convergence of tunnel section (mm)	10.7	10.37	10.69	3.01%

Table 3 Errors on predicted value and group B of measured value

Indicators (unit)	Measured value R2	Predicted value on BPNN P_b2	Predicted value on GA-ResNN P_a2	E2 (%)
Soil strength of foundation pit (MPa)	0.28	0.22	0.28	18.99%
Tension of anchor cable (kN)	284.9	282.45	284.32	0.66%
Strut axial forces of steel (kN)	168.6	156.77	162.75	3.55%
Load near foundation pit (kPa)	220	213.01	220.21	3.08%
Groundwater level (m)	63.01	63.86	62.39	0.37%
Accumulated horizontal displacement of supporting pile (mm)	7.99	6.68	7.44	9.55%
Accumulated bottom heave (mm)	4.8	4.18	4.60	8.77%
Buried depth of existing tunnel (m)	9.9	9.16	9.72	5.74%
Vertical distance between foundation pit and existing tunnel (m)	4.1	3.83	4.16	5.01%
Convergence of tunnel section (mm)	10.6	10.37	10.56	1.86%

Table 4 Errors on predicted value and group C of measured value

Indicators (unit)	Measured value R3	Predicted value on BPNN P_b3	Predicted value on GA-ResNN P_a3	E3 (%)
Single excavation depth of diaphragm wall (m)	2.4	2.23	2.39	6.90%
Single excavation length of diaphragm wall (m)	1.5	1.21	1.4	12.47%
Deformation modulus of soil in reinforced area (MPa)	10.2	12.56	10.46	20.34%
Single excavation area (m^2)	6	4.80	4.90	1.69%
Exposure duration at bottom of foundation pit (h)	16	12.31	16.99	16.82%
Change rate of groundwater level (mm/d)	−0.125	−0.07	−0.11	32.70%
Horizontal displacement rate of supporting pile (mm/d)	0.035	−0.03	−0.01	51.71%
Accumulated vertical displacement of supporting pile (mm)	3.09	2.09	2.63	17.78%
Vertical displacement rate of supporting pile (mm/d)	0.16	−0.02	0.13	93.97%
Horizontal displacement rate of diaphragm wall (mm/d)	0.0375	−0.30	0.19	498.35%

Table 5 Errors on predicted value and group D of measured value

Indicators (unit)	Measured value R4	Predicted value on BPNN P_b4	Predicted value on GA-ResNN P_a4	E4
Single excavation depth of diaphragm wall (m)	2.4	2.22	2.46	4.65%
Single excavation length of diaphragm wall (m)	1.8	1.20	1.59	22.06%
Deformation modulus of soil in reinforced area (MPa)	11.7	12.20	11.71	4.15%
Single excavation area (m^2)	7.2	4.80	5.20	5.55%
Exposure duration at bottom of foundation pit (h)	16	12.22	15.04	17.61%
Change rate of groundwater level (mm/d)	0.0275	0.14	0.019	390.12%
Horizontal displacement rate of supporting pile (mm/d)	0.1075	−0.03	0.11	126.46%
Accumulated vertical displacement of supporting pile (mm)	2.92	2.19	2.62	14.94%
Vertical displacement rate of supporting pile (mm/d)	−0.05	0.20	−0.08	432.72%
Horizontal displacement rate of diaphragm wall (mm/d)	0.2125	−0.14	−0.016	58.51%

$$E = \left(\left| \frac{P_b - R}{R} \right| - \left| \frac{P_a - R}{R} \right| \right) \times 100\% \qquad (2)$$

where P_b is the predicted value of BPNN, P_a is the predicted value of GA-ResNN, and R is the measured data.

Therefore, the prediction accuracy of GA-ResNN is better than that of BPNN along with the value of E gets larger.

The value of E in the first 10 sets of data is always positive according to Tables 2 and 3, while the average value of E is 4.17%. The value of E in the second 10 sets of data is

Table 6 Errors on predicted value and group E of measured value

Indicators (unit)	Measured value $R5$	Predicted value on BPNN P_b5	Predicted value on GA-ResNN P_a5	$E5$ (%)
Change rate of bottom heave (mm/d)	0.175	0.04	0.21	54.80%
Change rate of groundwater level (m/d)	−0.125	0.05	−0.13	134.74%
Accumulated ground settlement (m)	1.2	1.80	1.39	33.17%
Change rate of ground settlement (mm/d)	−0.125	0.07	−0.16	122.50%
Accumulated horizontal displacement of tunnel structure (mm)	6.62	6.19	6.77	4.23%
Horizontal displacement rate of tunnel structure (mm/d)	0.055	−0.09	0.04	239.83%
Accumulated vertical displacement of tunnel structure (mm)	4.91	4.77	4.79	1.75%
Vertical displacement rate of tunnel structure (mm/d)	0.0375	−0.12	0.04	387.16%
Accumulated horizontal displacement of supporting pile2 (mm/d)	7.56	7.21	7.44	3.05%
Change rate of ground settlement2 (mm/d)	−0.125	0.14	−0.13	203.47%

Table 7 Errors on predicted value and group F of measured value

Indicators (unit)	Measured value $R6$	Predicted value on BPNN P_b6	Predicted value on GA-ResNN P_a6	$E6$ (%)
Change rate of bottom heave (mm/d)	−0.025	0.20	0.0013	801.70%
Change rate of groundwater level (m/d)	−0.0255	0.03	0.0003	115.13%
Accumulated ground settlement (m)	1	1.80	0.95	74.67%
Change rate of ground settlement (mm/d)	0.0275	0.150	0.05	352.25%
Accumulated horizontal displacement of tunnel structure (mm)	6.52	6.31	6.56	2.63%
Horizontal displacement rate of tunnel structure (mm/d)	−0.025	0.14	−0.12	279.19%
Accumulated vertical displacement of tunnel structure (mm)	4.84	3.54	5.26	18.09%
Change rate of bottom heave (mm/d)	−0.0175	−0.14	0.02	433.36%
Change rate of groundwater level (m/d)	7.99	7.12	7.81	8.68%
Accumulated ground settlement (m)	0.0275	0.13	0.01	335.14%

always positive according to Tables 4 and 5, while the average value of E is 91.47%. The value of E in the last 10 sets of data is always positive except "Change rate of groundwater level" according to Tables 6 and 7, while the average value of E is 180.27%. GA-ResNN reveals abolutely advantages in front of the traditional BP model in predicting data.

According to Tables 2, 3, 4, 5, 6, and 7, results can be obtained as follows:

(1) The optimized GA-ResNN simulations correlate well with the field measurements while over 98.3% of E are positive. The network's prediction accuracy is determined by comparing the network predictions between two models (BP and GA-ResNN).

(2) Unstable results also occur occasionally (E is −0.38% in Table 7). The quality of prediction is determined by the discreteness of the input value. It can be concluded that a relatively accurate and stable result is presented in the rest of the data, while the average value of E is 91.97%.

(3) The predicted accuracy of the BP model is bad while the input values are negative, while the results of GA-ResNN are relatively accurate than that of the BP model.

(4) GA-ResNN shows its advantages while the input values have the characteristics of small change of gradient and small data.

Figure 6 shows the ratio curves of predicted errors on three models including BPNN, GA-BPNN, and GA-ResNN to measured data, respectively. The total number of model results is 60, and for the reason of a clear display, each 10 of them is grouped. The first ten pieces of data are named as group A; the second ten pieces of data are named as group B; the third ten pieces of data are named as group C; the fourth ten pieces of data are named as group D; the fifth ten pieces of data are named as group E; the last ten pieces of data are named as group F. GA-BPNN is the model without the residual training in GA-ResNN algorithm. Based on the predicted values in 2 days on 30 indicators. Standard

Fig. 6 Ratio of predicted errors on three training models to measured data: **a** group A, **b** group B, **c** group C, **d** group D, **e** group E, and **f** group F
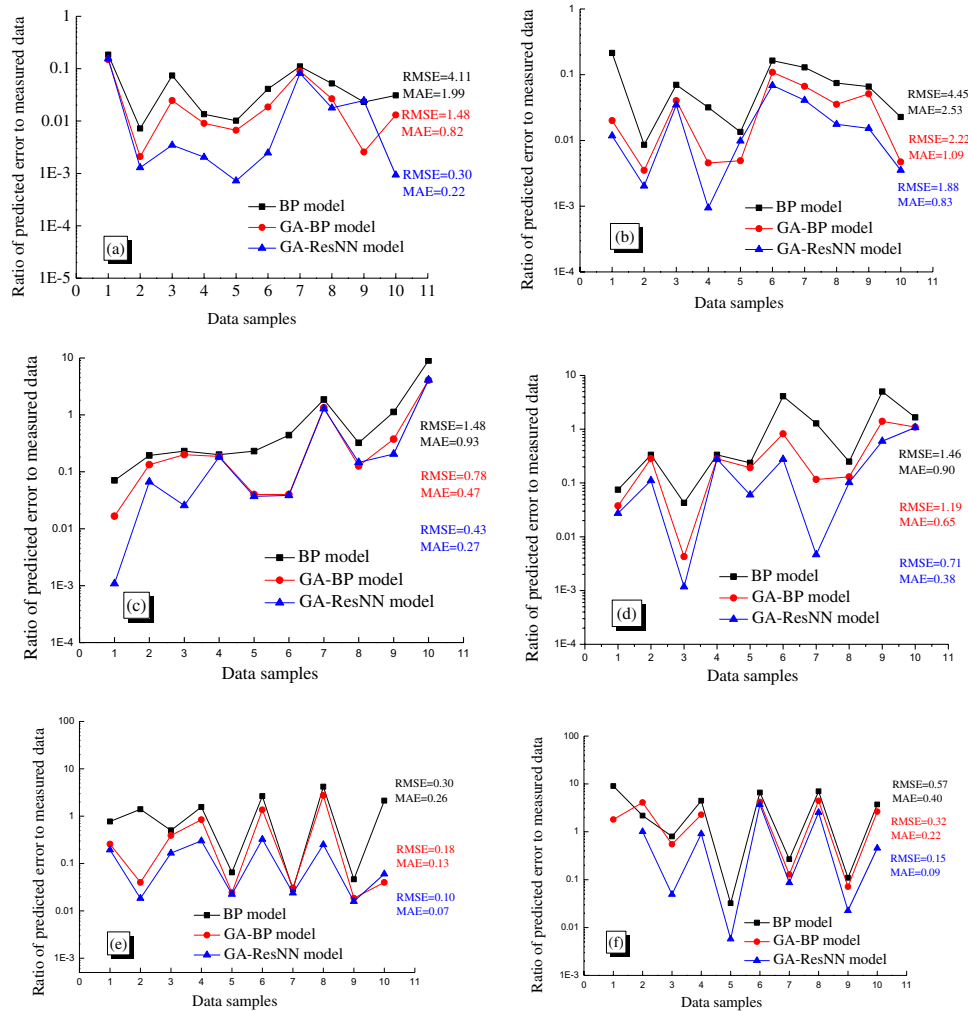
statistical errors *RMSE* (root mean squared error) and *MAE* (mean squared error) are also used for evaluation. One obtains:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}}$$
$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \qquad (3)$$

where *x* is the actual value, *y* is the predicted value, and *n* is the number of data.

The calculation results of the three models are given in Fig. 6. From top to bottom, the three groups of results correspond to the BP model, GA-BP model, and GA-ResNN model, respectively, in Fig. 6.

Results of analysis can be obtained as follows:

(1) The network trained using the proposed GA-ResNN algorithm gives a better correlation with the measured data than does the existing BP model and GA-BP models (the BP curve and GA-BP curve are above the GA-ResNN curve for the majority of the results). At the same time, the GA-ResNN model has the lowest *RMSE* and *MAE* values. Hence, predicted results with higher accuracy and veracity can be acquired by using the GA-ResNN prediction model.

(2) GA-BP also has a strong predictive ability, because when the results of the GA-BP model are very close to the measured data, the results of GA-ResNN are also in the similar conditions (curves of GA-BP and GA-ResNN overlapped according to Fig. 6 (c) and (d)). Even GA-ResNN does not perform as well as the GA-BP model in certain samples. However, when dealing with small data, GA-ResNN shows a better ability, so you need to choose a suitable prediction model according to the characteristics of the data.

(3) A suitable prediction model needs to be picked based on the charateristics of data samples. GA-ResNN shows a better ability in predicting dealing with small data compared with the other two training models.

Conclusions

The hybrid algorithm (GA-ResNN) which integrates the back propagation neural network (BPNN) with genetic algorithm (GA) and the idea of residual training can predict the trend of risk indicators of foundation pit relatively accurately. More accurate prediction data and higher operating efficiency can be obtained while data is classified according to the correlation during the pre-processing step. Through the optimization of genetic algorithm (GA) and ResNet, the BPNN model can quickly converge and drawback such as falling into local extremum can be avoided. Calculation speed and accuracy of ResNet are optimized by integrating with GA.

The hybrid GA-ResNN model gives more accurate prediction results than the GA-BP and BPNN models. In summary, the GA-ResNN model has a better feasibility in the prediction of foundation pit deformation no matter in practical engineering or scientific research. The inaccuracy produced by GA-ResNN while the initial data is negative needs to be further corrected. And the selection of training model also needs to be carried out after the analysis of the data features.

Declarations

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