Deformation Prediction of Landslide Based on Improved Back-propagation Neural Network

Article *in* Cognitive Computation · March 2012

DOI: 10.1007/s12559-012-9148-1

2 authors:

Huangqiong Chen

Zhigang Zeng
Huazhong University of Science and Technology

Cogn Comput (2013) 5:56–62
DOI 10.1007/s12559-012-9148-1

Deformation Prediction of Landslide Based on Improved Back-propagation Neural Network

Huangqiong Chen · Zhigang Zeng

Received: 12 November 2011 / Accepted: 19 May 2012 / Published online: 9 June 2012

Abstract In this paper, a modified method for landslide prediction is presented. This method is based on the back-propagation neural network (BPNN), and we use the combination of genetic algorithm and simulated annealing algorithm to optimize the weights and biases of the network. The improved BPNN modeling can work out the complex nonlinear relation by learning model and using the present data. This paper demonstrates that the revised BPNN modeling can be used to predict and calculate landslide deformation, quicken the learning speed of network, and improve the predicting precision. Applying this thinking and method into research of some landslide in the Three Gorges reservoir, the validity and practical value of this model can be demonstrated. And it also shows that the dynamic prediction of landslide deformation is very crucial.

Keywords Landslide prediction · Genetic algorithm · Simulated annealing algorithm · BPNN

Introduction

Undesired effects resulting from landslides on human life and economy of many nations are observed throughout the world. Mitigation of landslide hazards can be successful only when we have a detailed knowledge about the expected frequency, character and magnitude of mass movements in an area. Hence, the prediction of landslide regions is essential for carrying out quicker and safer mitigation programs, as well as future planning of the area. The rock-soil body of landslide is an open nonlinear system, and complexity is its essence attribute. Since the formation conditions, evolutionary process and deformation inducing factor of landslide own properties such as diversity, complexity and uncertainty of change, its mechanics behavior and deformation tendency correspondingly reflect the nonlinear characteristic which is the coexistence of determinacy and randomness[1]. The prediction of landslides is a difficult task to tackle, and it requires a thorough study of the past activities by using a complete range of investigative methods to determine the deformation conditions. However, most of the slope movements or potential failures may be predicted if proper investigations of parameters are made. The surface displacement deformation monitoring time series of landslide embody a concentrated reflection of this characteristic; therefore, they are usually used as the base of establishing theoretical model or criterion for time prediction of landslide. Currently, to solve such cutting-edge scientific issue as the landslide forecast and prediction, nonlinear theories and methods, which are effective in dealing with the complex problems, have been widely used, and a number of models and methods, which are based on the actual displacement monitoring time series, have been proposed. These studies not only greatly deepen our understanding to the complexity of landslide systems, but also promote the development of landslide forecasting theory powerfully.

Progress has been made in recent years in the ability to predict ground movement, but the state of art is deficient in many ways. On the basis of detailed investigation, a viable approach for the prediction of deformation displacement is necessary and an artificial neural network (ANN) comes in handy to fulfill this approach. ANNs are generic nonlinear

H. Chen (✉) · Z. Zeng
Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China
e-mail: chqkhs@163.com

H. Chen · Z. Zeng
Key Laboratory of Image Processing and Intelligent Control of Education Ministry of China, Wuhan 430074, China

function approximators, extensively used for pattern recognition and classification [2–8], which also have a wide applicability in system identification. ANN has developed rapidly in recent years. In particular, the back-propagation neural network (BPNN) can reveal the nonlinear relationship among the data samples. It has a lot of processing units to constitute a nonlinear adaptive dynamic system with good adaptivity, self-organization and strong abilities of learning, association, fault tolerance and anti-interference. The ANN approach has many advantages compared with other statistical methods; it is an effective way for forecasting in complex nonlinear dynamic systems. In recent years, the ANN is widely used in the area of landslide forecasting and predicting [9–14]. However, the back-propagation algorithm(BPA) which is the most widely used one among the ANN approaches currently has disadvantages such as lower convergence speed and easily getting into local minima points. [15–18]. Therefore, to solve these disadvantages, construction of an ANN model for predicting the deformation displacement is presented in this paper. The genetic algorithm (GA) refers to a model introduced and investigated by Holland [19] which uses the concepts of natural genetics in a specific way as an optimization. Every optimum solution 'evolves' through a series of generations. Each generation consists of a number of possible solutions to the problem, defined by an encoding. The fitness of each individual within the generation is evaluated and influences the production of the next generation. GA presents a robust method for searching for the optimum solution. The algorithm is mathematically simple yet powerful in its search for improvement after each generation. This algorithm has showed exceeding performance in obtaining global solutions for difficult nonlinear functions [20]. The application of the GA to one particularly complex nonlinear function, the ANN, has also showed to dominate other more commonly used search algorithms [21–23]. It has some main disadvantages such as slow convergence speed; premature convergence or stalling; the larger number of populations and individuals for some complex optimization problems. Simulated annealing algorithm (SA), which is based upon that of Kirkpatrick et al. [24], exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure and the search for a minimum in a more general system. The major advantage of SA over other methods is the ability of avoiding becoming trapped at local minima. It is a powerful optimization technique to solve the combinatorial optimization problems.

In recent years, the considerable progress has been made in last category. However, most of the previous researchers hybridized two of evolutionary techniques such as GA–BP, SA–BP and GA–SA. Little has fused GA, SA and BP synchronously. In this paper, we apply the combination of GA and simulated annealing algorithm to optimize the parameter of BP network architectures to determine the final architecture parameter, and then, a neural network modeling using back-propagation technique is proposed to predict the deformation of landslides. The results show that the method has very high prediction accuracy.

ANN Approach Based on Genetic-Simulated Annealing Algorithm for Landslide Prediction

Neural Network Architecture

BPNN is based on gradient descent algorithm, which was proposed by Rumelhart and McClelland [25]. It is a multi-layer network model, whose core is BPA. By interconnecting a proper number of nodes in a suitable way and setting the weights to appropriate values, a neural network can approximate any nonlinear function with arbitrary precision [26]. The BPNN consists of an input layer, several hidden layers and an output layer. Three-layer BPNN is used in this paper, and its architecture is shown in Fig. 1.

BPNN can reflect the relationship between the output and the input parameters accurately by training a large number of learning samples; therefore, it can achieve the purpose of optimizing the parameters and then realize predicting. The learning process of BPA consists of forward propagation and back propagation. When it is in forward propagation, the input information is transmitted to the output layer through the hidden layer. The state of each layer of neurons only affects that of the next layer. If the desired output cannot be obtained in the output layer, the BPNN switches to back propagation, and the error signal is sent back along the original connection path. When the BPNN is in back propagation, in order to reduce the error, the weights of each layer are modified one by one. Then, it switches to forward propagation. This process is iterative until the error is smaller than the given value.

BPNN is currently the most widely used algorithm for connectionist learning. For example, it has ideal effects in

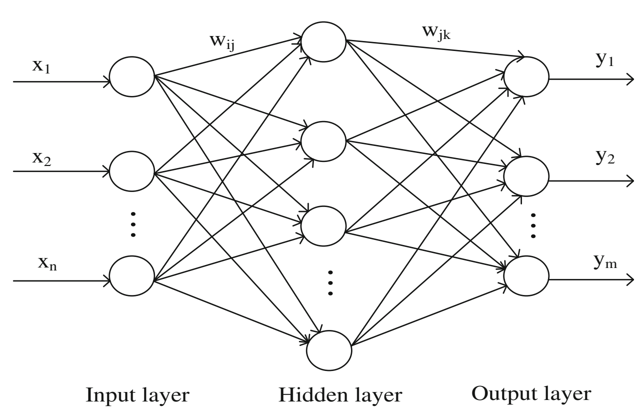

Fig. 1 Architecture of three-layer BPNN

pattern recognition, process control, fault diagnosis, function approximation and prediction because of its simple structure and the ability to approximate any continuous nonlinear function with arbitrary precision. BPNN has been successfully used as a mapping and prediction tool in the geotechnical engineering field. The network can be used to estimate functions from sample data as in the statistical technique [27]. However, as the learning algorithm of BPNN is based on the gradient descent method, its performance depends on initial conditions, and it has low convergence speed and is easy to get into local minima points.

When a data stream is analyzed via a neural network, it is possible to detect important predictive patterns which are not previously apparent to a non-expert. Therefore, the neural network can act as an expert. The particular network can be defined through three fundamental components: transfer function, network architecture and learning law [28]. It is essential to define these components to solve the problem of prediction satisfactorily.

A BPNN-based predictive model is to be developed to predict the future values of deformation displacement of landslides, based on the previous monitoring data. The proposed neural network model is a three-layer network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer, as shown in Fig. 2. The sigmoid transfer function is defined as:

$$f(x) = \log \mathrm{sig}(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

The linear transfer function is defined as:

$$f(x) = \mathrm{purelin}(x) = x. \tag{2}$$

Improved BPNN Modeling

Owing to the disadvantages of BPNN, this paper uses the combination of GA and simulated annealing algorithm to improve the BPNN. The algorithm can be briefly described as following: Firstly, the model optimizes the weights and bias of BP network by using GA. Secondly, in order to obtain proper weights and bias of a fixed network structure, we adopt SA algorithm with a certain probability to determine the real part of weights and bias of corresponding chromosome. The better weights and bias can be got by using SA global search, avoiding being trapped in a

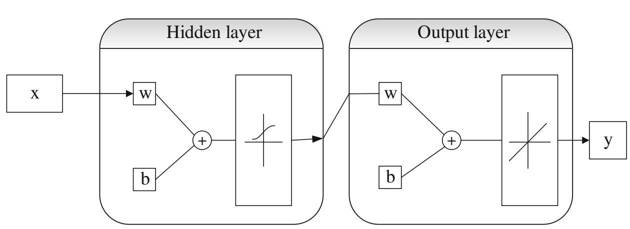

Fig. 2 Neural network architecture for the predictive model

local minimum when adjusted by BP algorithm. Finally, set new weights and bias obtained by SA to corresponding chromosome and then go to the next generation operation. The chart flow of the genetic-simulated annealing algorithm to train the neural network weights is shown in Fig. 3, and the main steps are as follows.

Step 1. The weights and biases are parameters of the neural network, and the real number coding method is adopted. Use a 3-layer neural network, in which the numbers of input nodes, hidden nodes and output nodes are n, p and m, respectively. So the length of the encoding is

$$l = (n + 1)p + (p + 1)m \tag{3}$$

We have one input variable (time) and one put variable (displacement). So in Eq. (3), n equals 1, and so does m.

Step 2. Assign values to the initial simulated annealing temperature T_0 and annealing rate λ. The number of iterations $k = 0$.

Step 3. Set the range of the connection weights of neural network to $[w_{\min}, w_{\max}]$, and assign the even-distributed random numbers which are generated in this interval to the individuals. This process creates the initial population.

Step 4. Decode the initial population, and calculate the network output by applying BP algorithm.

Step 5. Evaluate the individuals in the population, and decode the individuals. Assign the values obtained by decoding to corresponding connection weights (including the node biases). Introduce the learning samples, and calculate the learning error E. Define the individual's fitness as follows

$$f = 1/(1 + E) \tag{4}$$

In Eq. (4), $E = \sum_{i=1}^{M} \frac{1}{2}(d_i - y_i)^2$, where M is the number of training samples, y_i is the output of the neural network under the ith input sample, and d_i is the desired output of the response.

Step 6. Selection operation. Use the proportional selection operator, set the population size to S, and then, the probability of individual with fitness f_i selected into the next generation is

$$P_i = f_i \Big/ \sum_{i=1}^{S} f_i \tag{5}$$

Retain the individual with the highest fitness.

Step 7. Crossover operation. Because we adopt the real number coding, so we choose arithmetic crossover operator. The individuals X_1 and X_2 in parent take the crossover operation with a probability of P_c, and offspring can be generated as follows

$$X_1^{'} = eX_1 + (1 - e)X_2 \tag{6}$$

and

$$X_2^{'} = (1 - e)X_1 + eX_2 \tag{7}$$

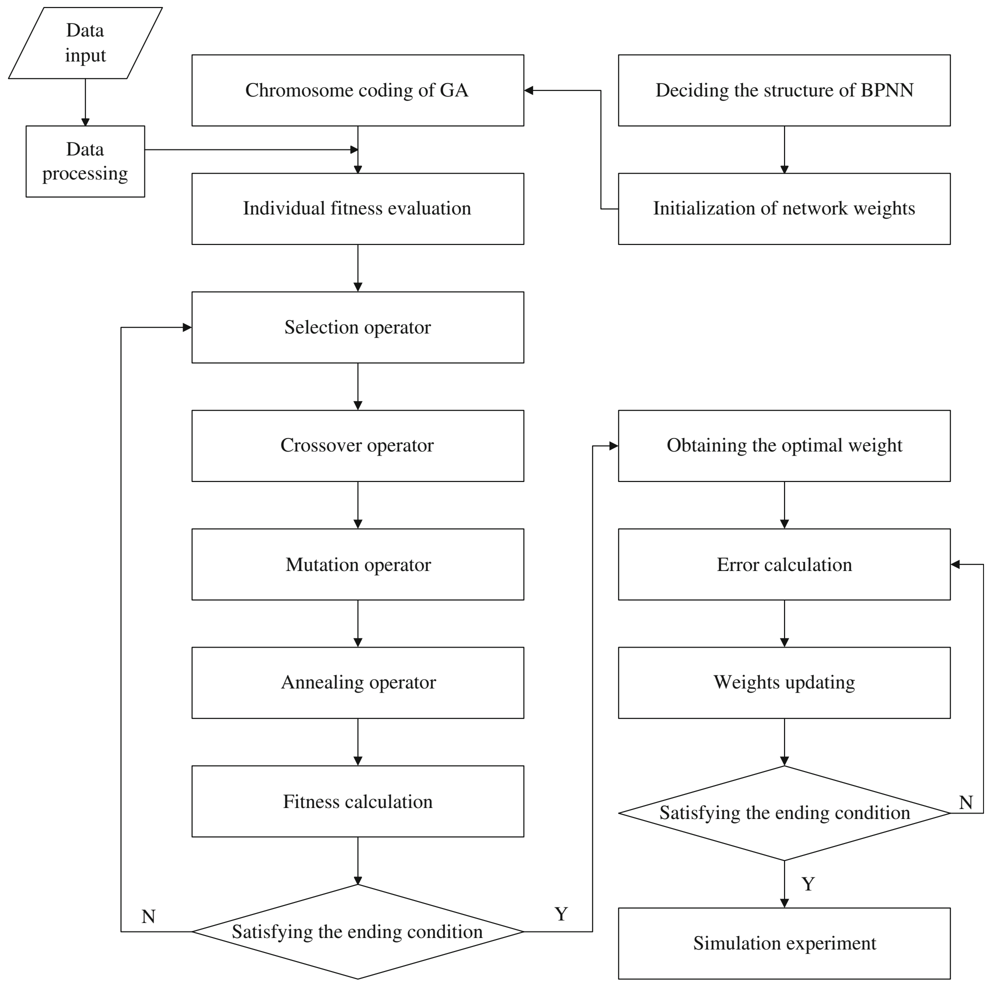

Fig. 3 GSA-BP algorithm flow chart

where e is a scale factor, generated by the even-distributed random number in (0, 1).

Step 8. Mutation operation. Use uniform mutation operator, each gene of the individual mutates with the mutation probability P_c, that is, replace the original value by even-distributed random number in the interval $[w_{\min}, w_{\max}]$ with the probability P_c.

Step 9. Introduce the optimal reserved strategy.

Step 10. Take simulated annealing operation to each individual in the population.

(a) Use the simulated annealing state to generate the new gene value $g'(k)$, $g'(k) = g(k) + \beta$, where $\beta \in (-1, 1)$, it is stochastic disturbance;
(b) Calculate the difference ΔC between the objective function value of $g'(k)$ and that of $g(k)$;
(c) Calculate the reception probability: $P_r = \min[1, \exp(-\Delta C/t_k)]$;
(d) If $P_r >$ random[0, 1), $g(k) = g'(k)$, otherwise, $g(k)$ remains constant;
(e) Introduce the optimal reserved strategy;
(f) Use the simulated annealing function $t_{k+1} = \lambda t_k$ to anneal.

Step 11. Decide whether the GA ending condition is satisfied. If it is satisfied, go to Step 11; otherwise, go to Step 4.

Step 12. Decode the optimal individuals searched by GA, and assign them to the weights of the neural network (including node bias), and then make prediction.

The primary purpose of the processes is to find the optimal individuals through genetic-simulated annealing algorithm, and use them to optimize the weights and biases of the neural network, which can decrease the instability of the network and increase its prediction accuracy.

Case Study

Area Description

In order to test the validity of the above forecast modeling, now this paper uses Baishuihe landslide as an example.

Table 1 ZG118 point accumulation displacement data

Time	Accumulation displacement (mm)	Time	Accumulation displacement (mm)
2003.08.01	92.3	2005.08.01	369.2
2003.10.01	100.1	2005.10.01	438.5
2003.12.01	107.9	2005.12.01	446.3
2004.02.01	115.4	2006.02.01	453.8
2004.04.01	121.7	2006.04.01	484.6
2004.06.01	169.5	2006.06.01	530.8
2004.08.01	246.2	2006.08.01	592.3
2004.10.01	284.6	2006.10.01	615.4
2004.12.01	300.1	2006.12.01	623.1
2005.02.01	301.2	2007.02.01	630.8
2005.04.01	303.5	2007.04.01	643.1
2005.06.01	330.8	2007.06.01	892.3

Baishuihe landslide is located on the south bank of Yantze River, which belongs to the Three Gorges reservoir and it is 56 km away from the Three Gorges Dam. The bedrock geology of the study area mainly consists of sandstone and mudstone, which is an easy slip stratum. The slope is of the category of bedding slopes. Slippage and deformation of the bedding slope are easily to occur under external forces such as tectonic joint cutting, incised unloading and edge collapse loading of the Yangtze River, and rainfall and so on. Baishuihe landslide is an old landslide, and bedding slope failure occurs frequently in the history. The warning area of Baishuihe landslide is large in scale and is the category of forward slopes. In August 2004, as the landslide had significant deformation, 85 people of 21 households in this area moved out. Currently, there are massive farmlands and citrus orchards in the slope. Once the slope failure of the warning area occurs, the safety of the inhabitant in reservoir area and shipping will be under serious threat, and the riverside highway will be destroyed. Considering the morphological and geological conditions of the Baishuihe landslide, it is evident that slope stability processes are the most relevant problem for public safety and land use.

Analysis and Results

Deformation observed data are shown in Table 1. This example uses three-layer BPNN (1, p, 1) to learn and forecast the data of Table 1. Increasing the number of neurons requires more computation, and this has a tendency to over fit the data when the numbers are set too high, but it allows the network to solve more complicated problems. We continuously increase both the number of neurons in the hidden layer until the network performed well in terms of the mean square error (MSE) and the error autocorrelation function. After several trials, the best number of hidden neurons is determined to be 15. The anterior data of 16 time steps are used to build up model and the latter data of 8 time steps for prediction. The parameters in this algorithm are set as follows: The hidden neuron number $p = 15$, evolution algebra is 50, the population size is 50, the crossover probability is 0.6, the mutation probability is 0.001, the initial annealing temperature $T_0 = 10{,}000$, and the annealing rate $\lambda = 0.9$. According to the model designed and the procedures of algorithm in "ANN Approach Based on Genetic-Simulated Annealing Algorithm for Landslide Prediction" section, 10 random experiments would be done. When using momentum BPA, iterations of BP training reaches 2,500, the mean of training MSE is 0.1254e-004, and the mean of testing MSE is 0.1254. However, when using GA–SA–BP algorithm, the iterations of BP training decrease to 100, the means of training MSE and testing MSE are 3.8720-005 and 0.0297, respectively. The fitted curve obtained by the improved BPNN is shown in Fig. 4. And the calculation

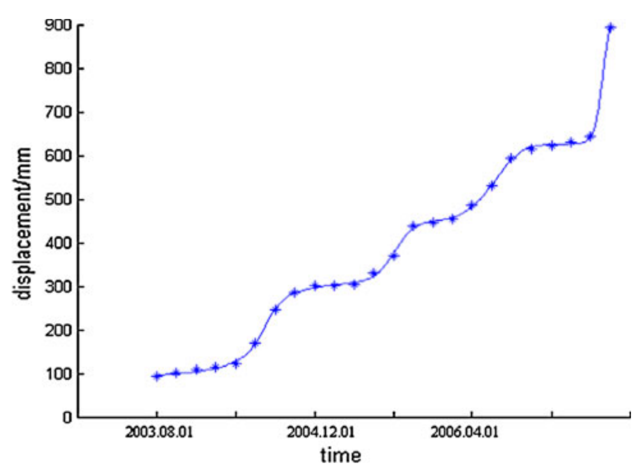

Fig. 4 The fitted curve obtained by improved BPNN

Table 2 ZG118 displacement comparison between predicted values and actual measurement value

Time	Actual measurement value (mm)	Predicted value (mm)	Absolute error (mm)	Relative error (%)
2006.02.01	453.8	471.14	17.34	3.82
2006.04.01	484.6	490.66	6.06	1.25
2006.06.01	530.8	533.72	2.92	0.55
2006.08.01	592.3	596.98	4.68	0.79
2006.10.01	615.4	614.48	0.92	0.15
2006.12.01	623.1	623.60	0.50	0.08
2007.02.01	630.8	632.12	1.32	0.21
2007.04.01	643.1	643.42	0.32	0.05
2007.06.01	892.3	892.71	0.41	0.05

result of Baishuihe landslide that achieved by using genetic-simulated annealing algorithm-improved BPNN modeling is shown in Table 2. From Fig. 4, we can see that the improved BPNN can train the data effectively and predict the displacement of the slope precisely.

As shown in Table 2, the predicting values and actual measurement values are very close for every calculation, and the relative error falls into 5 percent, the predicting precision is high enough which can satisfy the request of deformation prediction of landslide in medium-term and long-term.

Remarks: (1) Using multi-code which combines the GA, SA and BP perfectly can bring their individual advantages into play and complement with each other. As the GA–SA–BP algorithm makes use of GA population to do the research and probability combination of SA, random conjunction of GA, SA and BP directional search can reach the global optimization more easily; (2) let individual enter SA–BP by the reception probability, this heuristic method could greatly improve the speed of calculation and also guarantee the convergence of algorithm.

Conclusion

The predication and forecast of landslides is a complex and nonlinear question. The improved BPNN modeling can work out the complex nonlinear relation by learning models and using the present data. This paper adopted genetic-simulated annealing algorithm to optimize the architecture parameter of BPNN and obtained the relationship between output and input of the system by curve fitting.

The application shows that the BPNN model, which is optimized by genetic-simulated annealing algorithm, can achieve the better prediction result; therefore, this method has a good perspective in application and further development.

The formation of a landslide is not only influenced by internal factors, but also by external factors. The internal factors mainly include anisotropism of rock mass, high heterogeneity of rock mass structure and complexity of landform and geostress; the external factors consists mainly of the changes of underground water, rainfall and temperature, and the influence of human activities. When the monitoring time series data of displacement, underground water, rainfall, earthquake etc. are complete, the method in this paper can be used for susceptibility analysis of the effect on displacement that the changes of rainfall and underground water have.

Acknowledgments The work is supported by the Natural Science Foundation of China under Grant 60974021, the 973 Program of China under Grant 2011CB710606, the Fund for Distinguished Young Scholars of Hubei Province under Grant 2010CDA081, and the Specialized Research Fund for the Doctoral Program of Higher Education of China under Grant 20100142110021.

References

1. Huang ZQ. The nonlinear theories of landslide analysis and application. Zhengzhou: Yellow River Conservancy Press; 2005.
2. Gluege S, Hamid OH, Wendemuth A. A simple recurrent network for implicit learning of temporal sequences. Cogn Comput. 2010;2(4):265–71.
3. Subirats JL, Jerez JM, Gomez I. Multiclass pattern recognition extension for the new C-Mantec constructive neural network algorithm. Cogn Comput. 2010;2(4):285–90.
4. Rao S, Aleksander I. A position identification and path labelling mechanism for a neural model of visual awareness. Cogn Comput. 2010;2(4):360–72.
5. Indiveri G, Chicca E, Douglas RJ. Artificial cognitive systems: from VLSI networks of spiking neurons to neuromorphic cognition. Cogn Comput. 2009;1(2):119–27.
6. Garagnani M, Wennekers T, Pulvermueller F. Recruitment and consolidation of cell assemblies for words by way of Hebbian learning and competition in a multi-layer neural network. Cogn Comput. 2009;1(2):160–76.
7. Haikonen POA. The role of associative processing in cognitive computing. Cogn Comput. 2009;1(1):42–9.
8. Gros C. Cognitive computation with autonomously active neural networks: an emerging field. Cogn Comput. 2009;1(1):77–90.

9. Melchiorre C, Matteucci M, Azzoni A, Zanchi A. Artificial neural networks and cluster analysis in landslide susceptibility zonation. Geomorphology. 2008;94:379–400.
10. Pradhan B, Lee S. Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia. Landslide. 2010;7:13–30.
11. Lee S, Ryu JH, Kim IS. Landslide susceptibility analysis and its verification using likelihood ratio, logistic regression, and artificial neural network models: case study of Youngin, Korea. Landslides. 2007;4:327–38.
12. Pradhan B, Lee S. Landslide susceptibility assessment and factor effect analysis: backpropagation artificial neural networks and their comparison with frequency ratio and bivariate logistic regression modeling. Environ Model Softw. 2010;25:747–59.
13. Gao W, Feng X. Study on displacement predication of landslide based on grey system and evolutionary neural network. Rock Soil Mech. 2004;25(4):514–7.
14. Neaupane KM, Achet SH. Use of backpropagation neural network for landslide monitoring: a case study in the higher Himalaya. Eng Geol. 2004;74:213–26.
15. Jaroudi E, Makhoul J. A new error criterion for posterior probability estimation with neural nets. In: Proceedings of iteration joint conference on neural networks; 1990, pp. 185–192.
16. Ducker H, Cuny YL. Improving generalization using double back propagation. IEEE Trans Neural Netw. 1992;3(6):991–7.
17. Mayoraz F, Vulliet L. Neural networks for slope movement prediction. Int J Geomech. 2002;2(2):153–73.
18. Das SK, Basudhar PK. Prediction of coefficient of lateral earth pressure using artificial neural networks. Bundle A Electron J Geotech Eng. 2005; 10.
19. Holland J. Adaptation in natural and artificial systems. University of Michigan Press; 1975.
20. Zhu QM. A back propagation algorithm to estimate the parameters of non-linear dynamic rational models. Appl Math Model. 2003;27:169–87.
21. Arifovic J, Gencay R. Using genetic algorithms to select architecture of a feed forward artificial neural network. Phys A. 2001;289:574–94.
22. Harri N, Teri H, et al. Evolving the neural network model for forecasting air pollution time series. Eng Appl Artif Intell. 2004;17:159–67.
23. Li SJ, Li Y. A GA-based NN approach for makespan estimation. Appl Math Comput. 2007;185:1003–14.
24. Kirkpatrick S, Gerlatt JCD, Vecchi MP. Optimization by simulated annealing. Science. 1983;220:671–80.
25. Rumelhart DE, Hinton GE, McClelland JL. A general framework for parallel distributed processing: explorations in the microstructure of cognition, vol. 1. Cambridge: MIT Press; 1986.
26. Hornik KM, Stinchcombe M, White H. Multilayer feedforward networks are universal approximators. Neural Netw. 1989;2:359–66.
27. Agrawal G, Frost JD, Chameau JLA. Data analysis and modeling using artificial neural network. In: Proceedings of XIII international conference of soil mechanics and foundation Engineering, New Delhi; 1994, p. 1441–1444.
28. Simpson PK. Architecture neural system-foundation, paradigm, application and implementation. New York: Pergamon Press; 1990.