Prediction of Excavation and Settlement of Shallow-buried Tunnel Based on Radial Basis Function Neural Network of Human Brain

Xiaoping Cao

Abstract

Artificial neural network technology is to simulate the neural network structure of the human brain so as to solve the nonlinear engineering problem information processing system by establishing artificial neurons and sensors. The ground surface settlement caused by the excavation of shallow-buried tunnels is a research hotspot in the field of tunnels and underground engineering. By analyzing the influence factors that cause ground surface settlement, this study selects seven factors such as the cohesion and internal friction angle of surrounding rock as input and takes the measured value as the output to establish a ground surface settlement prediction model based on radial basis function neural network (RBFNN). A genetic algorithm is introduced to eliminate the slow convergence speed and local optimum of RBFNN. RBFNN prediction model can predict the ground surface settlement caused by the excavation of shallow-buried tunnels. The relative error of prediction is controlled within ±9%, and the prediction results meet the actual needs of the project. This study can provide reference for the expansion and application of RBFNN of human brain cortex in the engineering field.

Key Words: Radial Basis Function Neural Network, Genetic Algorithm, Shallow-buried Tunnel, Settlement

Introduction

Artificial neural network (ANN), also known as neural network, is a network consists of a large number of processing units that are widely interconnected. It is the abstraction, simplification, and simulation of the human brain, and reflects the essential characteristics of the human brain. It is regarded as an information processing system that can simulate the human brain's way of thinking with strong nonlinear mapping ability and learning ability. It has strong adaptability to nonlinear engineering problems, especially shows great advantages in the processing of a large amount of random data and multi-sample data prediction. ANN is popular because of its computational power and learning historical data through training (Devogelaere, Rijckaert, Leon, and Lemus, 2002). The neurons in the adjacent layer of ANN pass the signal from one layer to the adjacent layer through weighted links. The digital weight of these links is applied to the input of neurons and the required output signal is obtained by repeatedly adjusting the weight. ANN has hidden nodes between the input and output layers, but there is no specific method to obtain the number of hidden nodes. Usually, the suitable number of nodes is obtained through attempt and wrong basis to provide the best results (Lashkarbolooki et al., 2012; Li et al., 2018; Isah et al., 2017).

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At present, ANN has been widely used in many fields (Fu, 2003; Huang and Liu, 2016; Krizhevsky et al., 2012; Li et al., 2013; Shamseldin et al., 2007; Tian et al., 2012). The implementation of neural networks, such as the promotion of neural networks, regularization, cross-validation, learning methods, local minimum problems and dimension problems, can be found in various references. (Crucianu et al., 2001; Lampinen and Vehtari, 2001; MacKay, 2014; McLoone and Irwin, 2001; Wang et al., 2007; Zhang and Friedrich, 2003). At the same time, there have been further studies and improvements, and many technologies have been adopted to improve the generalization ability of the neural network model (Caruana et al., 2000; Hagiwara and Kuno, 2000). The ANN algorithm has also been widely used in geotechnical engineering. The prediction studies on the stability of slope rock mass, settlement of buildings, excavation of deep foundation pits through ANN can be found in various literatures. Jia Yipeng et al., predict rock burst by improving recursive neural network based on particle swarm optimization. Feng Xiating et al., use ANN and system science methods to conduct intelligent evaluation and space-time prediction of rock engineering safety under complex conditions. Li Yanjie et al., predict and analyze the excavation deformation of foundation pits based on genetic algorithm-BP neural network. Shen Qiang predicts the displacement of the side slope based on RBFNN. And Deng Zisheng introduces RBFNN into the inverse displacement analysis of deep foundation pits, realizing the use of measured displacement value to obtain the inversion of soil parameters.

The ground surface settlement and harm to surrounding buildings caused by the excavation of urban subway tunnels is one of the most difficult problems in engineering field. Based on the standard application of ANN in the engineering field, this study introduces RBFNN into the prediction of ground surface settlement caused by mined tunnels of urban subway. Combined with engineering practice, a large amount of measured data is used as a training sample to train RBFNN so as to achieve deep learning of RBFNN, realize settlement prediction of excavation of shallow-buried tunnels, and expand the application of artificial intelligence system in the engineering field.

Neural network

Artificial neural network (ANN) is one of the artificial intelligence (AI, is defined as a computer or other machines need human intelligence activities in the implementation of the ability), also known as the software or virtual sensor, this method has been widely used in games, automation, medical, process control, and other applications. In process control, its application has recently been used not only to model and control, but also to evaluate tools that are difficult to measure (called estimators). It is a kind of computational algorithm, which is used to predict the unmeasured parameters which have important significance in the system state feedback control law.

ANN can stimulate the structure and function of the human brain with the ability of processing information in parallel, distributed storage, and self-learning and reasoning. It is featured in fault-tolerance, nonlinearity, non-locality, and non-convexity, which is suitable for the identification and mapping of fuzzy information or complex nonlinear relationships. ANN establishes the artificial neuron structure, receives external information through sensors, and analyzes the research object information by numerous neurons constituting a neural center to identify the analyzed object. In geotechnical engineering, the ground surface settlement caused by the excavation of subway tunnels is a research hotspot in the field of underground engineering. The mechanical properties of ground surface settlement and surrounding rock, especially the cohesion and internal friction angle are closely related. Therefore, through the analysis data of multi-sample ground surface settlement, the deep learning function of neural network algorithm is used to learn the known sample data. The neural network structure is established, and then the ground surface settlement is predicted according to the relevant parameters of the research object so as to realize the application of the neural network algorithm technology in the underground engineering construction field. This study adopts RBFNN theory. RBFNN is a feed-forward neural network consisting of three layers of network topology, including the input layer, hidden layer, and output layer. The topology of neurons of RBFNN is shown in Figure 1:
obtained from RBFNN’s structure chart:

\[ w = \exp \left( \frac{h_i}{c_{max}} \| x_k - c_i \|^2 \right) \]  

(4)

**Genetic algorithm**

Genetic algorithm is a search algorithm which is established by simulating the genetic evolution process in the biological world. It embodies the competition mechanism of "survival competition and survival of the fittest".

The basic idea of genetic algorithm is to search from a group of randomly generated initial solutions, namely "populations". Each individual in the population is a solution to the problem, which is called a "chromosome"; genetic algorithm evaluates the chromosome through "fitness value". The probability of a chromosome with large fitness value is large and the probability of a chromosome with small fitness value is small. The selected chromosomes enter the next generation; the chromosomes in the next generation produce new chromosomes through crossover inheritance and mutation, namely "offspring"; after several generations, the algorithm converges to the best chromosome which is the optimal or nearly optimal solution to the problem.

The genetic algorithm selects the appropriate fitness function to evaluate the quality of the parameter solution. The next generation solution will be generated by copying, crossover, and mutation between different parameter solutions. In this process, in accordance with the law that individuals that adapt to environmental changes during the course of biological evolution can survive and individuals that don’t adapt to environmental changes will be weeded out, the solutions with low fitness value are gradually weeded out, and solutions with high low fitness value are retained. The genetic algorithm continues to iterate to obtain the solutions with the highest fitness value so that the optimal solution or nearly optimal solution of the problem is obtained. The
realization process of genetic algorithm is shown in Figure 2:

![Figure 2. Realization process of genetic algorithm](image)

**Genetic algorithm- neural network prediction model**

**Prediction process**

According to the mutual improvement of the genetic algorithm and RBFNN, the deep learning of the measured sample data of the ground surface settlement is realized, and a genetic algorithm-neural network prediction model is established. Firstly, the initial weight and threshold optimal solution of RBFNN are obtained by genetic algorithm. Then, the learning of the multi-sample data is realized via RBFNN, and the ground surface settlement is predicted. The specific implementation steps are as follows:

1) Modeling

The genetic algorithm is used to realize the optimal solution of the initial weight threshold of RBFNN. Firstly, 720 input variables are used to establish the RBFNN model.

2) Generation of initial population

Initial string structure data is randomly generated and each string structure data is an individual. N individuals constitute a population that iterates as the initial point;

3) Fitness value calculation and setting

The square sum and reciprocal of the difference between the predicted output value and the expected value of the neural network as the fitness function, as shown in formula (5):

$$J = \frac{1}{\sum_{i=1}^{N} (F(x_i) - F^*(x_i))^2}$$

(5)

Where, $F^*(x_i)$ is the predicted output value; $F(x_i)$ is the expected value, and $N$ is the number of predicted sample.

4) The value of fitness is obtained by different individuals for selection, cross, and mutation, and new populations are obtained continuously;

5) Repeat the above steps until the requirements are met or the maximum number of iterations is reached.

**Model learning**

The ground surface settlement caused by mined tunnel construction is affected by factors, including cohesion, internal friction angle, moisture content, rock weight, tunnel depth, distance from the midline of the tunnel, distance from the face, and time of the tunnel surrounding rock. According to the measured data of the mined tunnel of an interurban railway, the above factors are used (the tunnel is excavated by using the CRD method, so the progress is slow, and the daily progress is one meter. Therefore, the numerical distance from the face is consistent with the time, so both are combined into one influence factor. There are seven influence factors in total) as the input layer of the neural network model. The first five factors are the physical mechanics parameters of surrounding rock in the tunnel area and the buried depth of the tunnel, as shown in Table 1. The measured ground surface settlement value is used as the output layer of neural network, as shown in Figure 3. 90 groups (10 days in total) are randomly selected as a neural network learning sample.

**Table 1. Physical mechanics parameters of surrounding rock in the tunnel area**

<table>
<thead>
<tr>
<th>Cohesive force</th>
<th>Internal friction angle</th>
<th>Moisture content</th>
<th>Weight density</th>
<th>Burial depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>kPa</td>
<td>°</td>
<td>/%</td>
<td>/kN·m⁻³</td>
<td>/m</td>
</tr>
<tr>
<td>20.1</td>
<td>15.2</td>
<td>24.1</td>
<td>18</td>
<td>10</td>
</tr>
<tr>
<td>19</td>
<td>14.2</td>
<td>23.6</td>
<td>17.8</td>
<td>12</td>
</tr>
<tr>
<td>18.9</td>
<td>14.6</td>
<td>24.5</td>
<td>18.3</td>
<td>13</td>
</tr>
</tbody>
</table>
Figure 3. Settlement curve of a certain section (only partial data is listed in the space chart)

Based on Matlab programming language, a genetic algorithm-neural network ground surface settlement prediction model has been established. The RBFNN is trained by learning samples to establish a nonlinear relationship between input layer neurons and output layer neurons. Five sets of ground surface settlement data are selected as test samples. Then the settlement values and prediction value of the 75th day are compared, as shown in Figure 4.

Figure 4. Comparison curve of ground surface settlement

It can be seen from Figure 4 that the relative error between the predicted and measured value of the neural network is within -7.39%~+8.53%, and the prediction accuracy meets the engineering requirements, which verifies the validity of the established neural network prediction model. Besides, the model established by using genetic algorithm and RBFNN is featured in fast convergence and accurate prediction.

Figure 5. Geographical location of the project

Engineering Project
Engineering background
Civil engineering III TJ-15 of Phase I of Lanzhou Rail Transit Line 1 includes one station, one section and one line. It is located at Donggang East Road, Fanjiawan Village, Chengguan District, Lanzhou City, from Lanzhou Donggang Community to Jiuquan Hongshun Logistics Company. From west to east, it is 836.92 meters from Gongxingdun to Jiaojiawan, 506.52 meters of Jiaojiawan Station and 232.76 meters of Donggang Section. The total length is 1576.2 meters. The geographical location is shown in Figure 5.

The surface layer in the front section of the mined tunnel is loess with an average thickness of 1~5 meters and the thickness of the section is approximately 10 meters. The middle section is sand and pebble layer, and the thickness is 5~15 meters with the average thickness of approximately 8 meters. The underlying one is cretaceous sand and mudstone layer. The pebbles are rich in quaternary dive with strong water permeability. Cretaceous sands and mudstones are poor in diagenesis. The original fractures and joints are developed and expansive. If the underground building structure is selected, the anti-leakage, expansibility of surrounding rock and ground surface settlement must be taken into consideration. The physical mechanics parameters of the surrounding rock are shown in Table 2.

Table 2. Mean values of physical parameters of the surrounding rock (new loess)

<table>
<thead>
<tr>
<th>Cohesive force</th>
<th>Internal friction angle</th>
<th>Moisture content</th>
<th>Weight density</th>
<th>Burial depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.8 KPa</td>
<td>15.7 °</td>
<td>20.6 %</td>
<td>15.2 kN·m⁻³</td>
<td>8 m</td>
</tr>
</tbody>
</table>

Prediction of ground surface settlement
Through the input of different physical mechanics property parameters of surrounding rock and the relationship between tunnel structure and surrounding rock (tunnel depth), the ground surface settlement after tunnel excavation is predicted and compared with measured data based on Matlab programming language and genetic algorithm-neural network ground surface settlement prediction model. The comparison between the predicted results and the measured results is shown in Figure 6.
It can be seen from Figure 6 that RBFNN model is used to predict the ground surface settlement caused by excavation of shallow-buried tunnels in Lanzhou rail transit. By comparing with the measured values, it can be seen that the relative error of the two is within -8.05%~+4.57%, which meets the safety construction requirements of the project.

Conclusions
Through combining genetic algorithm with RBFNN, the global search ability of genetic algorithm is used to solve the optimal initial weight threshold of RBFNN to eliminate the defect that neural network is easily trapped in local optimal solution. A genetic algorithm-RBFNN ground surface settlement prediction model has been established. The multiple ground surface settlement data is used to achieve deep learning of neural network prediction model, and to achieve the application of ANN technology in the field of tunnels and underground engineering field.

Using the established genetic algorithm-RBFNN ground surface settlement prediction model and combined with ground surface settlement caused by mined tunnel excavation in Lanzhou, the ground surface settlement caused by multiple factors is predicted. Then the measured data is conducted for comparative analysis. The neural network model can effectively predict the ground surface settlement caused by tunnel excavation.

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