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## Original Paper

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# BP Network for Predicting the TBM utilization

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**Abstract:** This paper proposed the idea of combining genetic algorithm (GA) with BP (back propagation) neural network, and establishes the TBM tunneling utilization prediction model based on BPNN-GA. Based on the analysis of rock parameters affecting TBM utilization, the rock mass grade, uniaxial compressive strength UCS and joint spacing DPW are selected as the input parameters for TBM utilization prediction. The TBM utilization prediction model based on BPNN-GA is established. The node number and super parameters of hidden layer are determined by empirical formula. The prediction results of bpnn-ga model are combined with the traditional BPNN model. The results show that, compared with the traditional BPNN model, BPNN has been improved under the optimization of genetic algorithm, the prediction accuracy on the test set is increased by about 8.95%, and the mean square error is reduced by about 60%. BPNN-GA model does not rely on specific data sets in prediction, showing good portability and generalization.

**Keywords:** tunnel boring machine; BP neural network; TBM utilization; genetic algorithm

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## 1. Introduction

As urban construction develops, TBM has become very important. As the TBM technology improves and tunnel projects tend to be deeper and longer in distance, TBM is more widely applied in tunnel construction through time.

TBM utilization is the ratio of TBM net excavation time to total working time, which is an important performance index. The utilization is about 5% under difficult and complex geological environment or accident in field occurs. In perfect working condition the utilization can rise to 55%. And most common utilization ranges from 20% to 30%. This indicates that the net excavation time of TBM is only 6 to 8 hours per day. Most of the working time is spent on the maintenance and repair of TBM. Meanwhile, staff transfer, initial payment and material transportation also take up part of the time. The total downtime usually accounts for 70-80% of the total time. TBM utilization rate can evaluate the construction progress and construction period, and indirectly provide scientific basis for the construction party to adjust the construction scheme in time. Researchers have established different prediction models for TBM utilization rate prediction.

Based on the data collected from Karaj tunnel, O. Frough[1] established the relationship between rock mass classification system and TBM utilization rate based on regression analysis. The study shows that the maximum downtime related to rock quality occurs in broken rock and fault zone (at this time, RMR is the lowest). In the region where RMR is about 60, the downtime is the shortest.

P. JAIN [2] established the relationship between rock RMR, uniaxial compressive strength (UCS) and TBM performance characteristics. The results show that the utilization rate of TBM is linearly related to the uniaxial compressive strength of rock, and the utilization rate of TBM reaches the maximum in the range of RMR between 40 and 75.

Marcelo G. Simões [3] established a TBM utilization prediction model based on fuzzy logic. The model takes the machine diameter, RMR, groundwater inflow velocity and rock mass quality index (RQD) as input parameters to determine the possible trend and correlation between rock mass properties and TBM utilization rate. The research shows that the higher the RMR, the machine diameter and the rock mass quality index, the higher the utilization rate of TBM. The greater the groundwater inflow speed, the lower the utilization rate.

O. Frough [4] applied RES (rock engineering system) to calculate the rock mass related downtime index GRDI based on the main rock mass properties, and the research shows that the rock related downtime index is closely related to the TBM downtime.

O. Frough [5] evaluated the main rock mass properties that affecting TBM utilization rate and discussed their influence on TBM utilization rate. Quartz and other abrasive minerals are easy to cause serious wear of TBM hobs, clay and viscous minerals are easy to cause TBM cutterhead blockage, and poor geological conditions are likely to cause tool failure and collapse accidents. Such rock mass characteristics have a great impact on TBM downtime, and then have a great impact on TBM utilization.

Gabriele Brino [6] summarized a variety of TBM utilization prediction models, such as NTNU model, QTBM model, correlation analysis, and obtained the best prediction model under different compressive strength  $\sigma_c$  range based on error analysis. When  $50 < \sigma_c < 100$  MPa, NTNU and qtbm models can be used. When  $100 < 150$  MPa, Alber equation and qtbm model are the best. If  $> 150$  MPa, NTNU and qtbm model and innaurato equation are the best.

S. Yagiz [7] established a TBM utilization rate estimation model based on RMR. The model was established basing on the relevant data of multiple TBM tunnels. It is found that the correlation between the utilization rate and RMR is the highest. In addition, the utilization rate also depends on the lithology, RMR, TBM type and other factors. Therefore, the utilization rate can be predicted by machine parameters and rock mass parameters besides RMR. This empirical model may be applied to similar tunnel projects and rock types.

Currently, the researches on TBM utilization rate prediction mainly focus on establishing the statistical relationship between the utilization rate and the geological or construction factors of rock mass by using the traditional regression analysis method. In view of the excellent performance of artificial intelligence method in TBM performance prediction and even in the whole geotechnical engineering field, the next direction of utilization research is to use artificial intelligence method to improve the accuracy and mine hidden association information.

In this paper, a TBM utilization prediction model is established based on the improved BP neural network algorithm. The genetic algorithm and the traditional neural network algorithm are combined, namely BPNN-GA algorithm. To predict TBM utilization, uniaxial compressive strength, surrounding rock grade and joint spacing are selected as input parameters. The above parameters are collected from the 4th bid section of Jilin Yinsong water supply project. The mechanical parameters of rock mass such as uniaxial compressive strength and brittleness are obtained by field coring and indoor test; the utilization rate and joint condition are obtained from the field construction records and rock wall geological sketch respectively; the machine parameters such as torque and thrust are obtained from the acquisition system of TBM

## 2. Methods

BP neural network is a commonly used machine learning method, which is suitable for dealing with the nonlinear relationship between key value data. It has good fault tolerance ability, self-learning and self-adaptive ability as well as generalization ability. However, BP neural network is easy to fall into local optimum, while genetic algorithm (GA) can find the

global optimal solution through efficient parallel heuristic search. Therefore, we adopt GA to BPNN optimization to effectively avoid the algorithm falling into local optimum and improve the prediction accuracy.

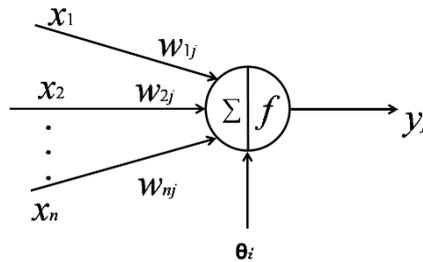
### 2.1. A brief introduction of BPGA-NN

Neural network is a mathematical model that imitates human brain or biological information processing mechanism in different degrees and levels. It integrates algorithm and structure, and is used to solve nonlinear and uncertain problems [8]. As shown in Fig. 1, BP neural network is a typical multilayer feedforward neural network. Its main characteristics are: the process of forward propagation of input data and the process of error back propagation constitute a learning process of BP neural network. Forward propagation makes the input information transmit to the output layer under the corresponding weight threshold and activation function. If the error between the output and the actual value exceeds the set value, the weight and deviation are modified by gradient descent for retraining using back propagation. The above process is repeated until the output value meets the sufficient accuracy [9]. The calculation process of hidden layer output and output layer output is shown in formula 1.1 [10] and equation 1.2 [10].

$$H_j = f_{hid}(\sum_{i=1}^n w_{ij}x_i - \theta_j), j = 1, 2, 3, \dots, m \quad (1.1)$$

$$O_k = f_{out}(\sum_{i=1}^n w_{jk}H_j - \theta_k), k = 1, 2, 3, \dots, l \quad (1.2)$$

where  $H_j$ ,  $O_k$  stand for the output of  $j^{th}$  hidden layer and output layer respectively.  $f_{hid}$ ,  $f_{out}$  stand for the activation function of hidden layer and output layer respectively.  $w_{ij}$  stands for the  $j$ -th weight parameter of  $i$ -th layer.  $\theta_j$  is the threshold value of network layer.  $x$  is the input of the network.



**Fig. 1 Neuron calculation diagram**

BP neural network uses parallel distributed processing of information. It has good fault tolerance, self-learning, self-adaptive and generalization capabilities. However, BP neural network also has shortcomings such as low convergence efficiency, easy to fall into local

minimums. The basic reason lead to different training results may be that BPNN is easy to fall into local minimums. Generally speaking, BPNN uses the gradient descent method to adjust the weighting parameters. This method optimizes the training errors along the direction where gradient decent. However, when the weighting parameters trap the network into a local minimums, the method cannot jump out of the local optimal solution for further search. Therefore, the method is more dependent on the initial weights of the network, resulting in limited training accuracy.

Different from BP neural network, genetic algorithm can effectively avoid the situation that the optimization process falls into local minimums. Genetic algorithm is a heuristic global randomized optimization method developed by referring to the evolution law of biological world. The basic principles are as follows. For a weight parameter, the genetic algorithm first generates  $n$  initial populations randomly, after appropriate decoding, the fitness of each individual in the population is evaluated by the adaptive function, and the individuals with high fitness will have a higher chance of replication, that is to copy all the information of the high fitness individuals to the next generation. In addition, two paired individuals are selected. According to the pre-set crossover probability, some genes of two individuals are exchanged with each other to generate new individuals. At the same time, mutation operator is introduced to replace the gene values of some loci in the chromosome coding string with other alleles on the loci, thus forming a new individual until the individual meets the needs.

On the one hand, genetic algorithm initializes a group of weight parameters randomly, which is regarded as a population, which means that the genetic algorithm is operated from many random points, rather than limited to a certain region; on the other hand, the genetic algorithm can carry out efficient heuristic search in the solution space, and at the same time, the probability is not limited to a certain area. Hence the optimal global solution is obtained by deterministic state transition rules. In addition, genetic algorithm also has the advantages of parallel computing, and does not rely on gradient information. Therefore, genetic algorithm and neural network algorithm can be nested to effectively prevent the weight parameters from converging to local minimum in model training.

Based on the above analysis, the optimization of BP neural network algorithm has precision, but as a single-point search method, BP neural network algorithm is easy to fall into the local optimal solution, while the genetic algorithm can evaluate multiple solutions in the search space, and has strong global search ability. Therefore, the initial solution of the optimal weight parameter can be obtained by genetic algorithm, and its decoding can be brought into the model training of BP neural network to obtain a better training model. Applying this training model to

the prediction of TBM utilization rate can not only ensure the accuracy of utilization rate prediction, but also avoid the problem that the BP neural network algorithm falls into local optimum [11] [12]. Fig. 2 is the flow chart of BPNN-GA algorithm.

**Fig. 3.2 Genetic algorithm optimization neural network algorithm flow**

Genetic algorithm searches the optimal solution of initial weight parameters of BP neural network through continuous iteration. Firstly, genetic algorithm needs to "code" the weight parameters in BP neural network, that is, the combination of weight parameters is transformed into a "chromosome". Selecting appropriate coding method can simplify the subsequent crossover and mutation operation of genetic algorithm. In this paper, according to the characteristics of parameters, the genetic algorithm is coded by real number coding to optimize the connection weights and thresholds of BP neural network. A coding string represents an individual, and several individuals constitute the initial population. The initial population performs the process of selection, crossover and mutation of genetic algorithm, and continuously generates a new generation of population. Real coded crossover is shown in Eq. 2.1 and Eq. 2.2: where C and D are the offspring of A and B, and t is a random number in the (0,1) interval.

$$C = A(1-t) + Bt \quad (2.1)$$

$$D = At + B(1-t) \quad (2.2)$$

After coding the weight parameters, the genetic algorithm optimize the weight parameters in follow steps:

1. Initialize the population. It includes mutation probability  $P_m$ , crossover probability  $P_c$  and crossover size; real number is used in coding, and the size of the initial population is set as 50;
2. Individuals are ranked according to the evaluation function. The evaluation function is used to measure the probability that an individual can survive in the whole population, that is, the ratio of individual fitness to population fitness. As shown in Eq. 3.1 [13]. The higher the individual's fitness, the easier it is to retain the individual, otherwise it is easy to be eliminated

$$P = \frac{f_i}{\sum_{i=1}^N f_i} \quad (3.1)$$

Mean square error (MSE) is an important index to evaluate BPNN prediction model. In genetic algorithm, the fitness value of an individual is an important index to evaluate the performance of an individual. If the sum of squares of the corresponding BPNN is  $E_i$ , then the fitness function of the individual is shown in Eq. 3.2 [13]

$$f_i = \frac{1}{E_i} \quad (3.2)$$

3. Select a certain number of individuals for replication. The number of individuals to be copied is determined by the size of fitness. Individuals with high fitness have more copies, while individuals with small fitness have fewer copies, while the total number of individuals in the population remains unchanged;
4. Some individuals were randomly selected for cross operation. By using the cross probability, the  $M_i$  and  $M_{i+1}$  cross operation produces new individuals  $M_i'$  and  $M_{i+1}'$
5. Randomly selected some individuals for mutation operation. The mutation of  $M_j$  produces a new individual  $M_j'$ ; that is, the alleles on the gene are randomly changed. Fitness function determines whether mutation makes individuals perform better;
6. The new individuals were added to the population and their fitness was evaluated
7. When the fitness of individuals in the population meet the requirements, the training is finished, otherwise, turn to step 3.
8. After the individual meets the relevant requirements, the final optimal individual is decoded.

### 3. TBM utilization prediction using TBM data from Water Supply Project on Songhua River

#### 3.1. Factors affecting utilization

Rock mass properties have great influence on the utilization rate. In recent years, many researchers have proposed utilization prediction models using different input parameters to predict the utilization rate. In the  $Q_{\text{tbn}}$  [14] [15] model, the tunnel diameter, rock mass classification and tool life span are used to predict the utilization rate. In this model, such as logistics, maintenance and groundwater interference are not considered. In CSM model [16] [17], RMR rock mass classification is main factor to estimate the utilization rate. In MCSM model [18] [19], DPW discontinuity and TBM downtime are used to evaluate utilization. Gong Qiuming [20] studied the relationship between the utilization rate of TBM and RMR based on

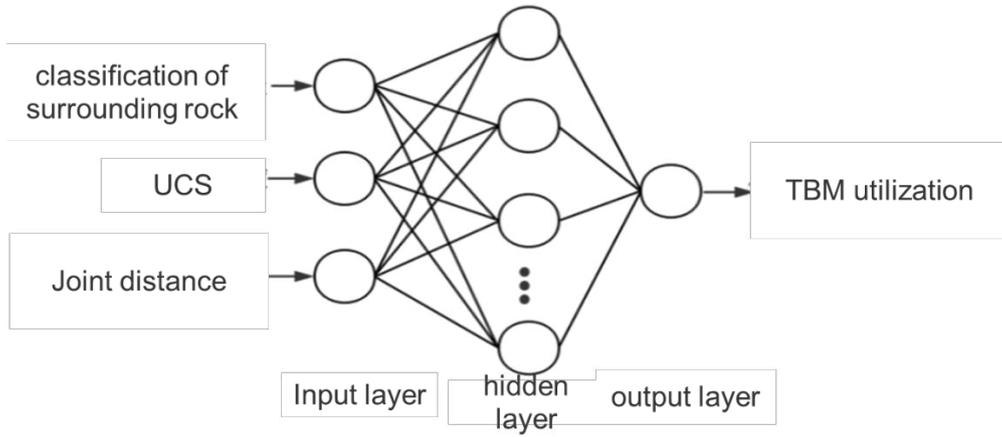
the rock mass properties of the tunnel and the rock mass classification system (RMR classification) relying on the Yinhanjiwei tunnel project.

The main geological factors affecting TBM utilization rate include rock mass quality classification, UCS and rock integrity. Among them, RQD rock mass quality classification, RMR rock mass quality classification, Q rock mass quality classification and surrounding rock grade are used to characterize rock mass quality classification, UCS and tensile strength are used to characterize rock mass strength, and joint spacing and joint angle are used to characterize rock integrity. Among them, rock mass quality classification has the strongest correlation with utilization ratio and have direct impact the utilization ratio [20] [21], the index of rock mass strength and TBM Excavation is closely related. Research shows that the performance of TBM is linearly related to UCS of rock [22]; the index representing the integrity of rock mass has a great impact on TBM tunneling. The research shows that when the joint spacing is too small, the rock strength and joint strength are roughly equal. When the hob acts on the rock mass, the cracks generated in the rock mass can directly reach the joint surface and form a through body. As a result, there may be landslides and falling blocks in the process of excavation, which will lead to the shutdown of TBM and the decrease of utilization rate. When the joint spacing increases, the rock breaking efficiency will gradually decrease, and the utilization rate will also decrease [23] [24]. To sum up, we select surrounding rock grade, uniaxial compressive strength and joint spacing as input parameters of utilization.

According to the change of surrounding rock grade, the whole tunnel is divided into 240 sections, and then the utilization rate of each section is calculated according to the daily construction records of each section. The information of surrounding rock grade, average rock mass parameters and average operation parameters corresponding to the section are obtained are used as the input parameter data in the utilization rate prediction.

### *3.2. Model architecture*

Using the neural network toolbox and genetic toolbox goat, the TBM utilization prediction model (BP model) based on BP neural network and the TBM utilization prediction model optimized by genetic algorithm (BPNN-GA model) are established in Matlab environment. The structure of BP neural network is shown in Fig. 2



**Fig. 2 BP neural network structure**

Funahashi [25] pointed out that if a three-layer neural network is used, the input layer and output layer use linear mapping function, and the hidden layer uses nonlinear incremental mapping function, then the network can be used to approximate any continuous function. Hence in this study, a three-layer BP neural network is applied.

The loss function is usually used to measure the training quality of the model. In this paper, mean square error (MSE) is adopted. Assuming the number of data samples is  $N$  and the training data (actual value) is  $Y_n$ . The predicted output value of neural network is  $\hat{Y}_n$ . Then the mean square error loss function of BP neural network prediction is shown in Eq. 4 [26]. The lower MSE indicates better accuracy on training set.

$$MSE = \frac{1}{N} \sum_{n=1}^N (\hat{Y}_n - Y_n)^2 \quad (4)$$

The neural network constructed in this paper has three input neurons and one output neuron. The three rock parameters including surrounding rock grade, UCS and joint distance are taken as the input parameters of the neural network. The training process of the neural network is to obtain the optimal weight and threshold value, so that the error between the predicted value and the actual value of TBM is minimized. All the weights and thresholds of the neural network are taken as one Solution vector. The solution vector is the individual in the population of genetic algorithm. In the genetic algorithm, 50 individuals are generated randomly as the initial population. Through mutation selection, a new population is obtained. After the genetic algorithm reaches the ideal precision (50 generations at most), the individuals with the highest fitness value are selected. The weight threshold of the optimized individuals

is taken as the super parameter of the neural network model Number. The specific program implementation is shown in Figure. 3

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**Algorithm 1** BPNN-GA algorithm for TBM utilization

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**Input:** training set: X, input dimension: R, hidden layer: S1, output layer: S2  
**Output:** util\_value

- 1: **for** each weight  $W1$  and threshold  $B1$  between input-hidden layer **do**
- 2:      $W1(i,j) = \text{value}(R*(i-1)+j)$
- 3:      $B1(i,1) = \text{value}((R*S1+S1*S2)+i)$
- 4: **end for**
- 5: **for** each weight  $W2$  and threshold  $B2$  between hidden-output layer **do**
- 6:      $W2(i,j) = \text{Num\_code}(S1*(i-1)+j+R*S1)$
- 7:      $B2(i,1) = \text{Num\_code}((R*S1+S1*S2+S1)+i)$
- 8: **end for**
- 8: **for** random individual  $p(i,j) \in \text{Pop}$  **do**
- 9:      $\text{cross\_Ind1} = p_i * \text{rand}() + p_j * (1 - \text{rand}())$
- 10:     $\text{cross\_Ind2} = p_i * (1 - \text{rand}()) + p_j * \text{rand}()$
- 11:    **if**  $\text{Mutation\_rate}(i,j) > \text{rand\_rate}$  **then**
- 12:      $p(i,j) = \text{Mut\_In}(p(i,j))$
- 13:    **end if**
- 14: **end for**
- 15: **for** each  $p(i,j) \in \text{Pop}$  **do**
- 16:     **if**  $\text{newIn\_fitRate} > \text{oldIn\_fitRate}$  **then**
- 17:      $\text{new Pop} = \text{update}(\text{old Pop})$
- 18:     **end if**
- 19:     **if**  $\text{fit\_rate}_{p(i,j)} > \text{best\_fit}$  **then**
- 20:      $\text{best\_fit} = \text{fit\_rate}_{p(i,j)}$
- 21:     **end if**
- 22: **end for**
- 23:     $\text{BPNN\_model} = \text{train}(X, \text{Pop}_{\text{best}}, \text{Learn\_rate}, \text{Training\_num}, \text{Precision})$
- 24:     $\text{util\_value} = \text{BPNN\_model}(\chi)$

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**Fig. 3 BPNN-GA pseudo code**

### 3.3. model implementary

In the training process of neural network model, the factors that affect the model performance mainly include two aspects: one is the network architecture, that is, the number of input layer, hidden layers and output layer; the other one is the connection weight between layers. The main factor affecting the network structure are the number of hidden layer nodes, learning rate and system error. The number of nodes in the output layer and input layer is generally determined by the system application, the number of nodes in the hidden layer is determined by the user's experience. Too few nodes will affect the accuracy of the network, and too many nodes will greatly increase the training time of the network model. It is necessary to train users to make a judgment according to the number of characteristic parameters of the

sample set and the network architecture. The learning rate in network model training means the iterative step size of the model during forward propagation or backward propagation. Generally speaking, the smaller the learning rate is, the smaller the step size is, the more epochs the model needs to be trained; if the learning rate is too large, the iterative step size will reduce the training time, but it will affect the accuracy of the network structure and cause large training errors. It is necessary to adjust the model parameters continuously to find the model with the minimum test error.

In BPNN-GA algorithm, for the selection of the number of neurons in the hidden layer, the number of neurons is set between 3 and 13 according to the empirical formula, and the optimal number of nodes is determined by error (MSE) analysis. The empirical formula is shown in equation 5:

$$h = \sqrt{m+n+a} \quad (5)$$

Where  $h$  is the number of hidden layer nodes;  $m$  is the number of input layer nodes;  $n$  is the number of output layer nodes;  $a$  is the adjustment constant between 1 and 10.

Firstly, set a small number of hidden layer neurons to train the network and record the prediction accuracy of the network; secondly, gradually increase the number of hidden layer neurons, and train with the same sample data, the number of hidden layer neurons that can make the output error of the network minimum is the optimal number of neurons; finally, through error comparison, it is concluded that the best effect is when the number of nodes is set to 10. The learning rate and the selection of activation function is tested through a large number of experiments, it turns out that when the learning rate is 0.01 and the activation function is Tansig function, the training effect of the network is the best. The specific parameter analysis is shown in Table 1.

In addition, for genetic algorithm, the size of the initial population, genetic generation, mutation rate, crossover rate has an impact on the prediction effect of the algorithm. In the process of parameter adjustment, population size is 10 ~ 50, step size is 10; iteration steps are 30 ~ 100, step size is 10; mutation rate is 0.01 ~ 0.05, step size is 0.01; crossover probability is 0.5 ~ 1, step size is 0.1, a total of 90 parameter groups are selected to test the combination of these parameters. The super parameters of the optimal model are shown in table 2.

**Table 1 The influence of the number of hidden layer neurons on the error**

Nodes of hidden layer	MSE
3	0.0994
4	0.0947

5	0.0873
6	0.0886
7	0.0875
8	0.0860
9	0.0837
10	0.0756
11	0.0799
12	0.0814

**Table 2 Algorithm parameter table**

parameter	value
Activation function of hidden layer	Tansig
Activation function of output layer	Tansig
optimizer	Gradient descent
Learning rate	0.01
Max iteration step	50
Population size	50
Genetic algebra	50
Variation rate	0.01
Mating rate	0.7

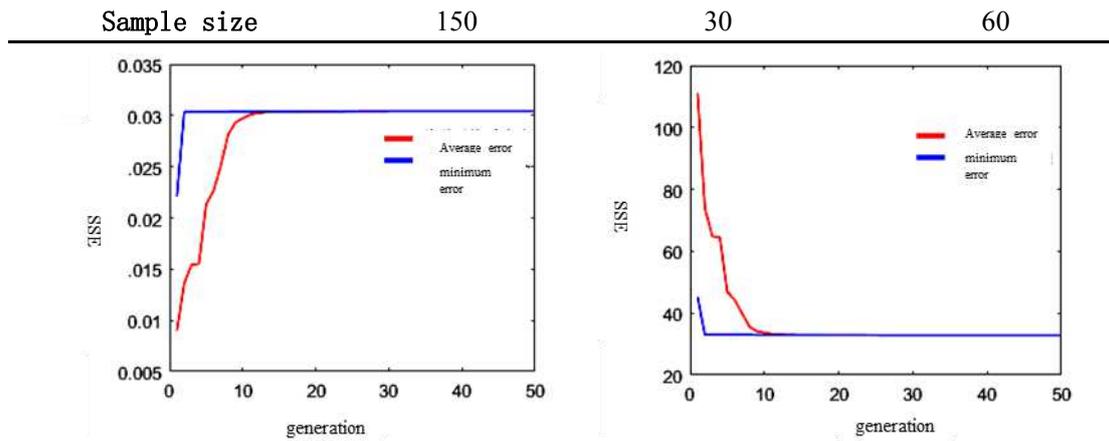
## 4. Results

### 4.1. Fitness and error analysis

According to the change of surrounding rock grade, the whole tunnel is divided into 240 sections. The utilization rate of the section and the corresponding surrounding rock grade, average rock mass parameters and average operation parameters are calculated according to the daily construction records of each section, and 240 groups of utilization data are obtained. 150 of them are randomly selected as the training set, 30 data point from the remaining 90 are randomly selected as the test set, and the last 60 groups of data are used as the validation set. Both the test set and the validation set data do not participate in the network training process, but are used to reflect the network prediction effect after the network training. Table 3 shows the percentage distribution of utilization datasets.

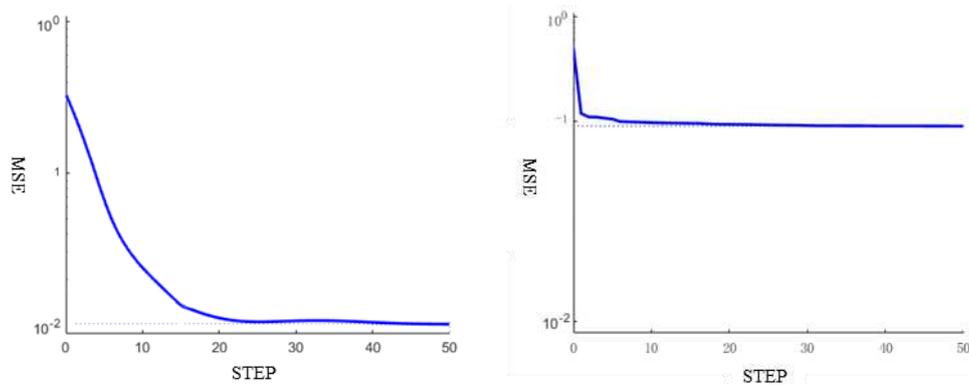
**Table 3 TBM utilization dataset usage percentage distribution**

	Training	Testing	Validation
percentage	62.5%	12.5%	25%



**Fig. 4 Fitness-Genetic Algebra Change Diagram and Error-Genetic Algebra Change Diagram**

As shown in Fig. 4, in genetic algorithm, the average fitness of the population reaches the maximum value in about 15 generations, and the sum of MSE also reaches the minimum value around 15 generations. The optimal individuals in the population are decoded as the initial network weight threshold of the neural network, and the initial weights of the neural network are trained by genetic algorithm, which can effectively avoid the occurrence of local optimum. But compared with BP neural network algorithm, due to the complex structure of BPNN-GA network, the data processing process involves encoding, decoding and other operations, which greatly increases the complexity of data processing, prone to a long time-consuming problem.



**Fig. 5 BPNN-GA and BPNN error-iteration step number graph**

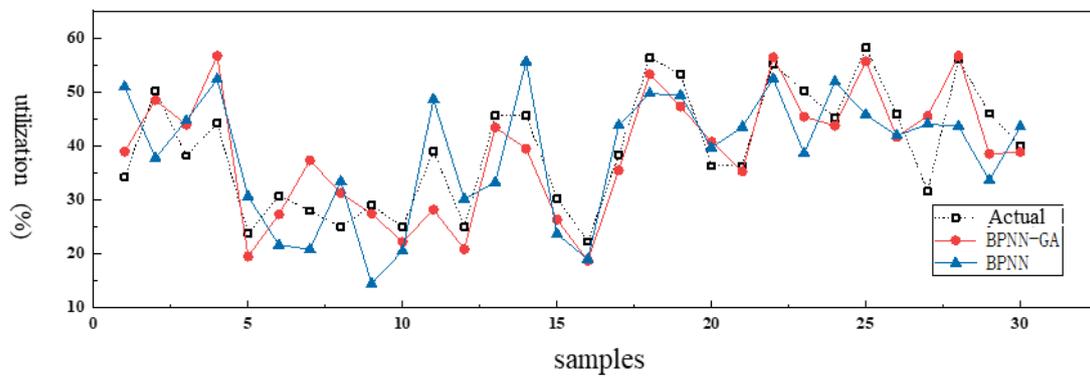
It can be seen from Fig. 5 that the error of BPNN will not decline when it reaches 0.1, which indicates that the traditional neural network algorithm has reached the local extreme value at this time. After optimization by genetic algorithm, the neural network can jump out of the local extreme value point and search for the global optimum. The error of the optimized neural network algorithm can reach about 0.01.

#### 4.1. Comparison of prediction accuracy

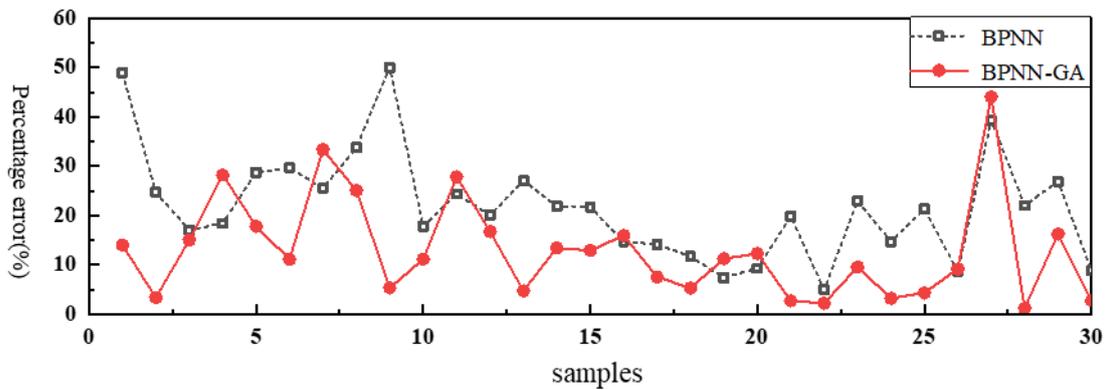
In order to compare the two algorithms and evaluate the prediction results directly and accurately at the same time, the MSE and the mean absolute percentage error (MAPE) were used to evaluate the prediction results of the two models. The comparison chart of predicted data and actual data of the two models is shown in Fig. 6(a), the absolute percentage error of single point prediction data is shown in Figure 6 (b), and the comparison chart of MSE of single point prediction data is shown in Figure 6 (c).

**Table 4 Model test set percentage error comparison chart**

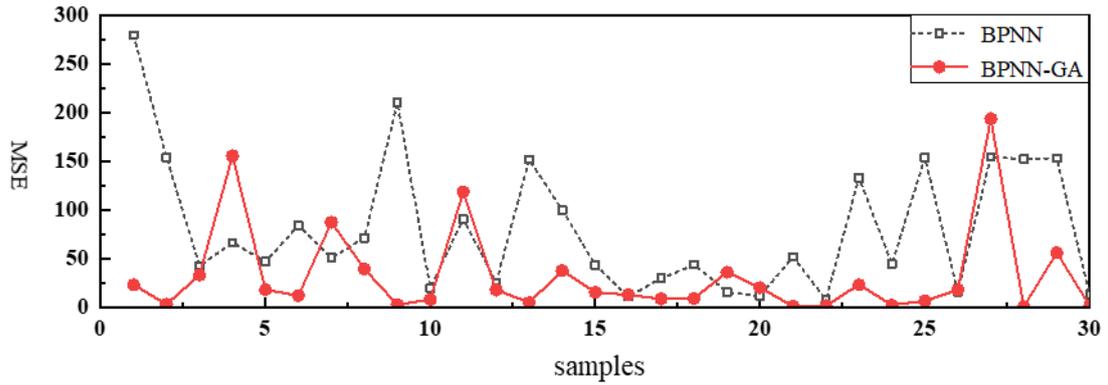
	BPNN	BPNN-GA
<b>MAPE</b>	21.89%	12.94%
<b>MSE</b>	80.9	32.14



(a)



(b)



(c)

**Fig. 6 (a) Comparison of actual data with traditional BPNN model and BPNN-GA model prediction data (b) Comparison of prediction percentage error between BPNN model and BPNN-GA model(c) Comparison of prediction mean square error between BPNN model and BPNN-GA model**

From table 4, it can be seen that the prediction accuracy of the traditional BP neural network model on the test set is 78.11%. The MSE is 80.9. The prediction accuracy of BPNN-GA model on test set is 87.06%. The MSE is 32.14. Compared with the traditional BP neural network model, the prediction accuracy of BPNN-GA model is improved by 8.95%, and the mean square error is reduced by about 60%.

From figure 6 (a), it can be seen that compared with the traditional BP neural network model, the change trend of predicted value and actual value of BPNN-GA model is more consistent. The traditional BPNN model has poor performance in many prediction points, such as the sample points with serial numbers of 9, 11 and 14.

From figure 6 (b), it can be seen that the percentage error of 17 sample points of the traditional BP neural network prediction value is more than 20%, the percentage error of 6 sample points is more than or close to 30%, and the maximum percentage error is 49.99%; while the percentage error of only 5 sample points is more than 20%, and the percentage error of 2 sample points is more than or close to 30%. The maximum percentage error is 44.05%. In addition, the percentage error of 22 samples predicted by BPNN-GA model is lower than that predicted by BP neural network.

From figure 6 (c), it can be seen that the mean square error of four sample points exceeds 50, the MSE of three sample points exceeds 100, and the maximum MSE is 155.7; as a comparison, the BPNN-GA of 16 sample points exceeds 50, the BPNN-GA of 9 samples exceeds 100, and the maximum BPNN-GA is as high as 279.9. In addition, the BPNN-GA of 22 samples of BPNN-GA model is lower than that of BP neural network. In conclusion, for the test set, after the optimization of genetic algorithm, BPNN-GA has achieved better prediction effect, and BPNN-GA model has better stability and higher fitting degree.

## 5. Discussion and Conclusion

In view of the disadvantage of BPNN easily falling into local minimum value, this paper selects GA optimized BPNN algorithm to predict the utilization rate. Through empirical formula, it determines the number of neurons in the hidden layer, and selects the super parameters. The TBM utilization prediction model based on BPNN and BPNN-GA is constructed by MATLAB. The MAPE and mean square error are used to compare the prediction results. The results show that, compared with BP neural network, both the stability and accuracy of the prediction results are improved under the optimization of genetic algorithm. Compared with the traditional BPNN prediction model, the accuracy of BPNN-GA model on the test set is increased by 8.95%, and the mean square error is reduced by about 60%. It shows that the BPNN-GA model in this paper is not picky in the selection of data, and has good generalization. However, when BPNN-GA is applied to predict TBM utilization rate, some data points still have low prediction accuracy. Therefore, in further research, we will focus on strengthening the research on the factors affecting TBM utilization, and constantly improve the prediction accuracy.

## 6. Conclusion

The geological conditions, rock mass properties, and machine parameters h

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**Conflicts of Interest:** The authors declare no conflict of interest.

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  - 27.

# Figures

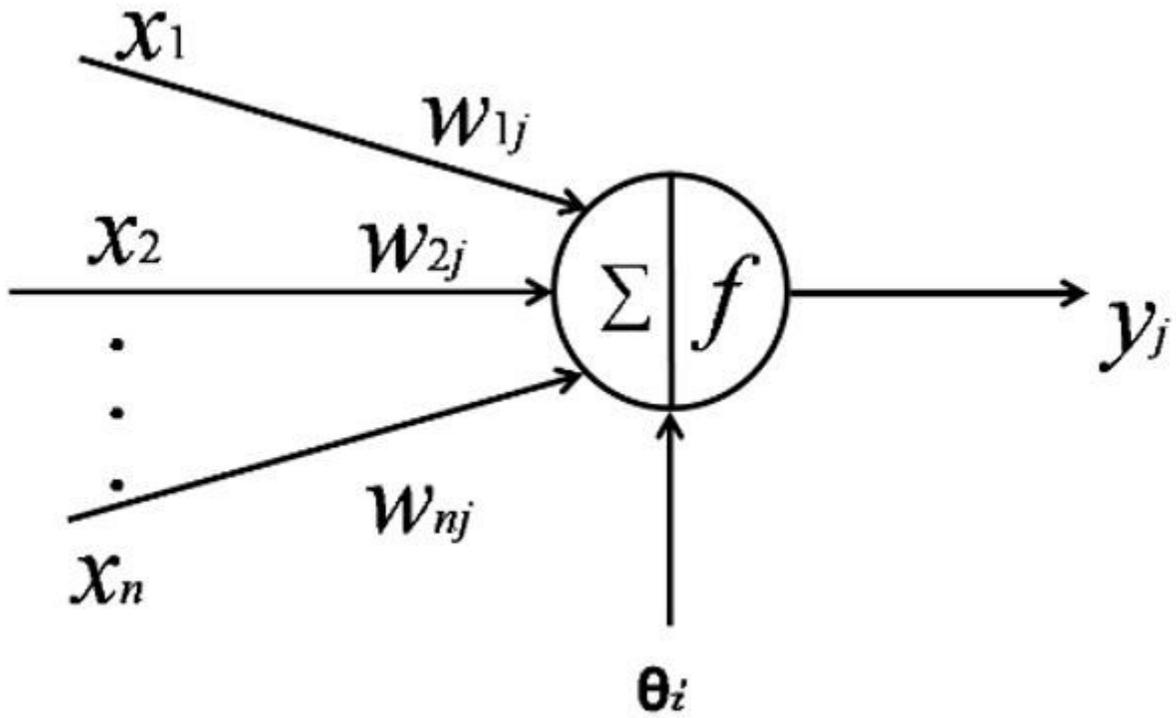


Figure 1

Neuron calculation diagram

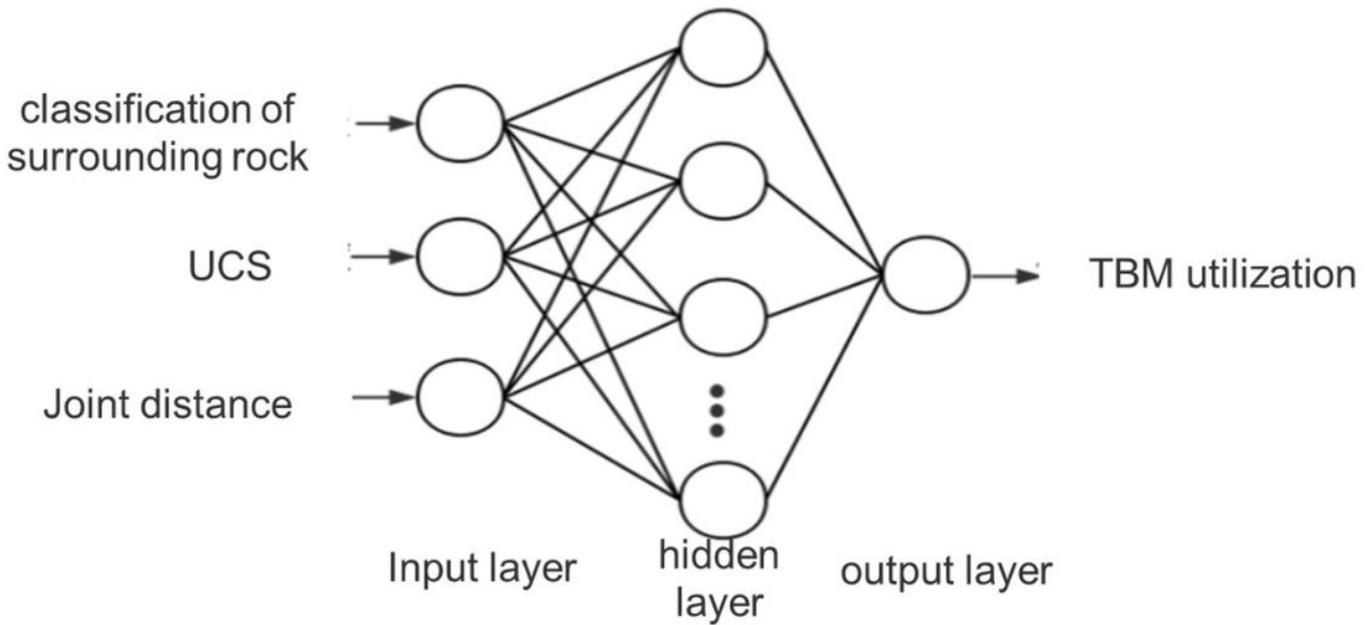


Figure 2

**Algorithm 1** BPNN-GA algorithm for TBM utilization

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**Input:** training set: X, input dimension: R, hidden layer: S1, output layer: S2  
**Output:** util\_value

- 1: **for** each weight  $W1$  and threshold  $B1$  between input-hidden layer **do**
- 2:      $W1(i,j) = \text{value}(R*(i-1)+j)$
- 3:      $B1(i,1) = \text{value}((R*S1+S1*S2)+i)$
- 4: **end for**
- 5: **for** each weight  $W2$  and threshold  $B2$  between hidden-output layer **do**
- 6:      $W2(i,j) = \text{Num\_code}(S1*(i-1)+j+R*S1)$
- 7:      $B2(i,1) = \text{Num\_code}((R*S1+S1*S2+S1)+i)$
- 8: **end for**
- 8: **for** random individual  $p(i, j) \in \text{Pop}$  **do**
- 9:      $\text{cross\_Ind1} = p_i * \text{rand}() + p_j * (1 - \text{rand}())$
- 10:     $\text{cross\_Ind2} = p_i * (1 - \text{rand}()) + p_j * \text{rand}()$
- 11:    **if**  $\text{Mutation\_rate}_{p(i,j)} > \text{rand\_rate}$  **then**
- 12:      $p(i,j) = \text{Mut\_In}(p(i,j))$
- 13:    **end if**
- 14: **end for**
- 15: **for** each  $p(i, j) \in \text{Pop}$  **do**
- 16:     **if**  $\text{newIn\_fitRate} > \text{oldIn\_fitRate}$  **then**
- 17:      $\text{new Pop} = \text{update}(\text{old Pop})$
- 18:     **end if**
- 19:     **if**  $\text{fit\_rate}_{p(i,j)} > \text{best\_fit}$  **then**
- 20:      $\text{best\_fit} = \text{fit\_rate}_{p(i,j)}$
- 21:     **end if**
- 22: **end for**
- 23:     $\text{BPNN\_model} = \text{train}(X, \text{Pop}_{\text{best}}, \text{Learn\_rate}, \text{Training\_num}, \text{Precision})$
- 24:     $\text{util\_value} = \text{BPNN\_model}(\chi)$

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Figure 3

BPNN-GA pseudo code

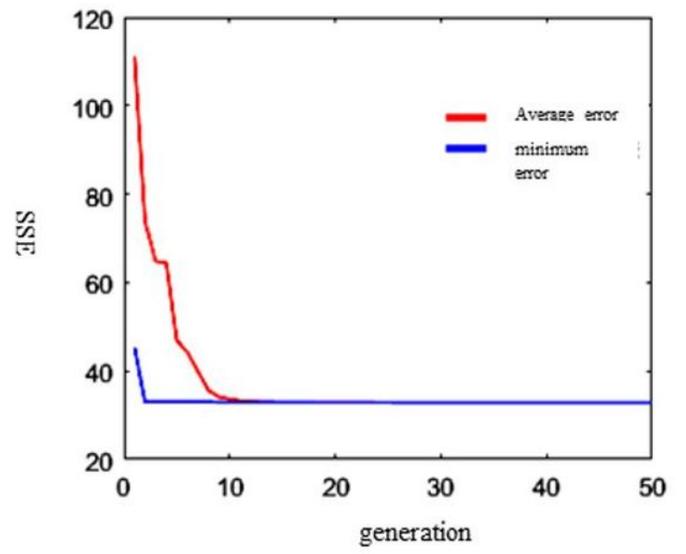
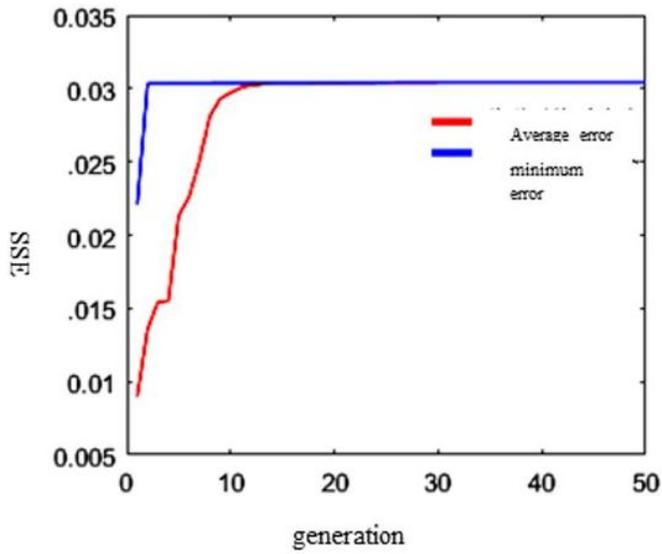


Figure 4

Fitness-Genetic Algebra Change Diagram and Error-Genetic Algebra Change Diagram

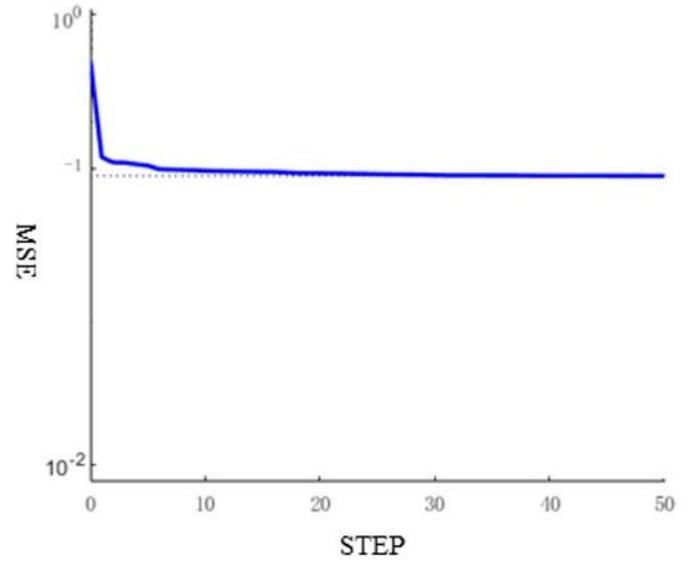
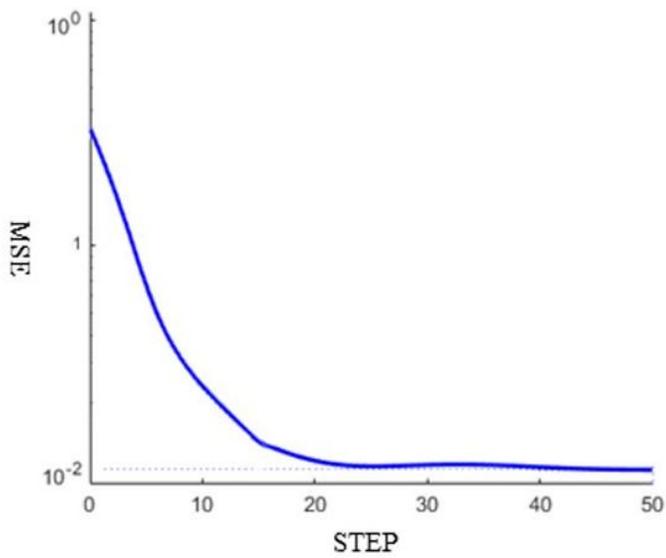
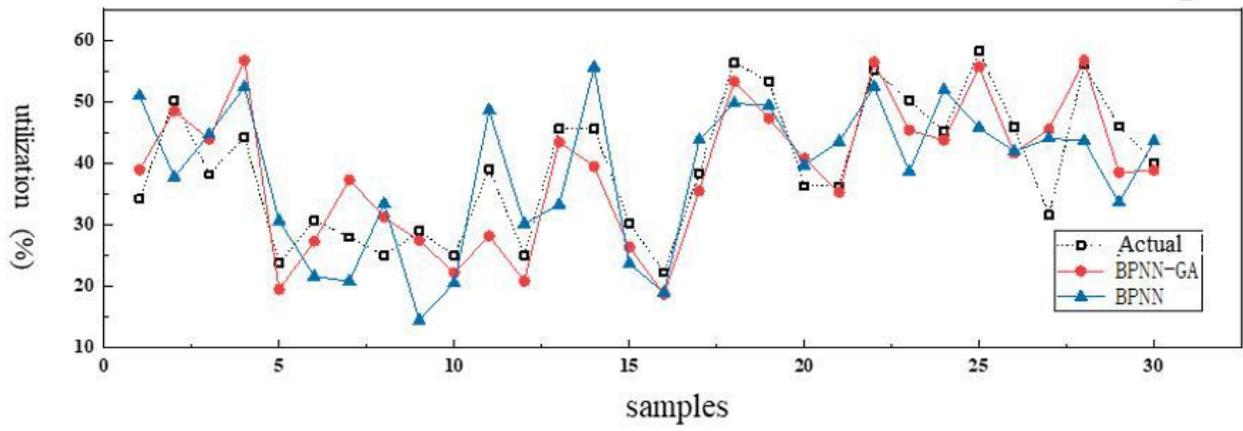
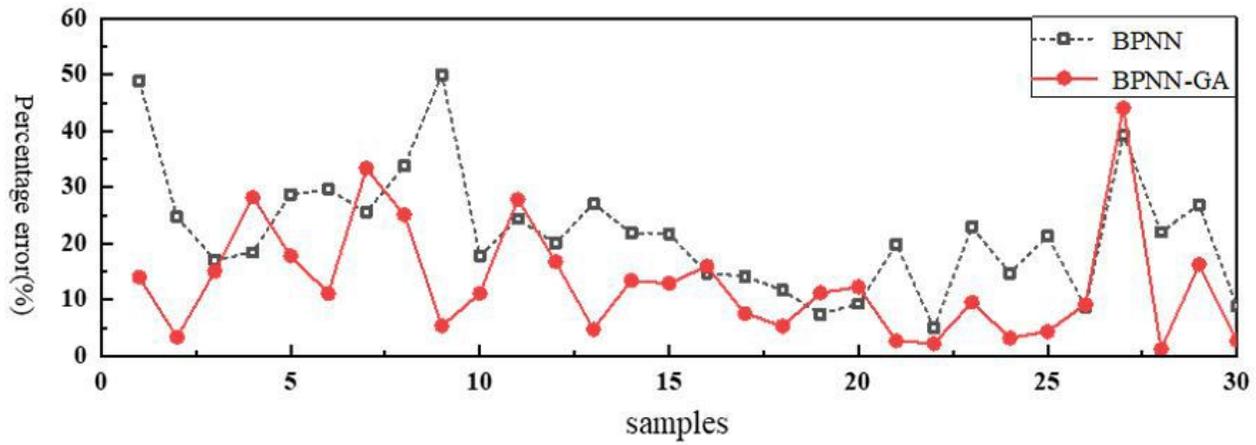


Figure 5

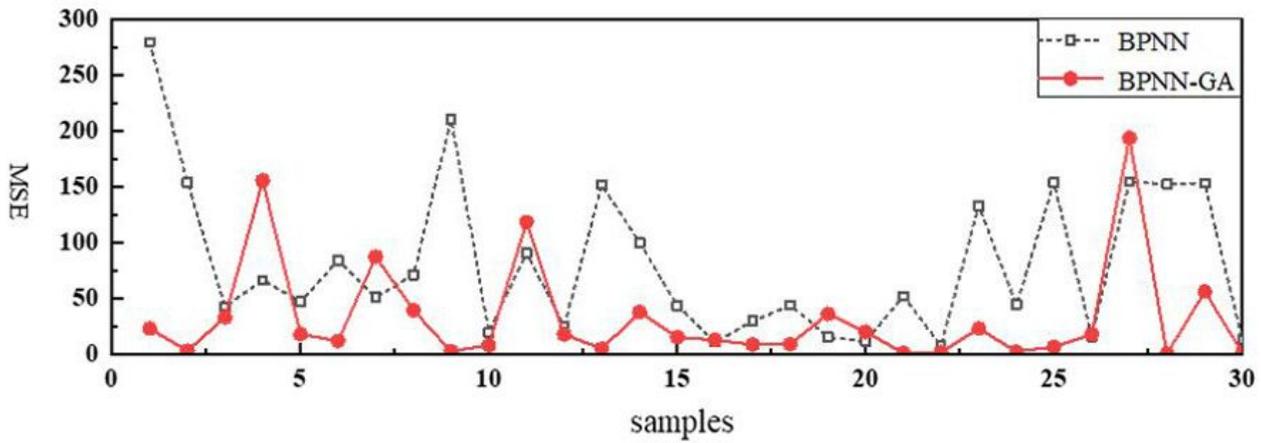
BPNN-GA and BPNN error-iteration step number graph



(a)



(b)



(c)

Figure 6

(a) Comparison of actual data with traditional BPNN model and BPNN-GA model prediction data (b) Comparison of prediction percentage error between BPNN model and BPNN-GA model (c) Comparison of prediction mean square error between BPNN model and BPNN-GA model