DOI: 10.21276/sjpms

Scholars Journal of Physics, Mathematics and Statistics **ISSN 2393-8056 (Print)**
Sch. J. Phys. Math. Stat. 2017; 4(3):121-126 **ISSN 2393-8064 (Online)**

Improve the Excavation Speed of the Tunnel Based on Genetic Algorithm— Radial Basis Function Network Algorithm

Chunliang Zhao[1], Shulin Sui[2]
[1,2]College of Mathematics & Physics, Qingdao University of Science & Technology, Qingdao 266061, China

***Corresponding Author:**
Chunliang Zhao
Email: 1690363925@qq.com

Abstract: The acceleration of the urban process poses new challenges to transport, the construction of three - dimensional traffic has become an important way to solve the congestion problem. The subway is an important factor in the appeal of a big city, however, the rapid and efficient mining of digging tunnels becomes the key to cost savings. The purpose of this paper is to optimize the use of excavation machines and maximize the potential of the development of shield machines, thus achieving savings in maintenance time and cost. For the impact of many factors and The existence of non-linear problems between the variables, we propose a radial basis function network with self-learning ability, which can fit the target and the target variable; In view of the problem that the training speed of RBF network learning method is slow, we introduce the genetic algorithm, and we propose a floating-point coding genetic algorithm based on the adaptive mechanism as a learning algorithm for RBF network learning. The final experimental results show that the accuracy of the new algorithm reaches 95.43%, while learning time significantly shortened by about 37%. All those proves that our algorithm is effective for predicting wear amount, which can improve the efficiency of the machine and save a lot of cost, it is valuable to promote.
Keywords: Tunnel optimization, GA-RBF, Three - dimensional traffic, nonlinear optimization problem

Introduction

Study significance

In recent years, the world has invested heavily in the subway construction. With the technological innovation, the traditional drilling outbreak tunnel construction has been gradually replaced by TBM, TBM has also been more widely applied to hard rock, broken rock and other complex formation conditions. In the actual tunneling project, it is necessary to estimate and forecast the TBM excavation rate PR, construction progress AR and tool life in advance for the feasibility study of the project, the economic utility evaluation, the construction progress forecast and the risk control.

Research status quo

The domestic research in this area is lagging behind, Rostami et al. Proposed the CSM prediction model based on the measurement of hob thrust in different types of rocks [1-2]. Bllindbeim, Bruland presented the NTNU model[3-4], Barton N put forward the QTBM system based on the original rock classification system Q system [5-6], Gong et al. proposed a specific rock mass load ability index model (SPMBI) from the principle of rock breaking [7], based on the uniaxial compressive strength (UCS) and the rock mass index (RQD), a new method based on multiple linear regression is proposed, which is based on the long - distance water conveyance tunnel constructed in three different rock formations in Iran and New Zealand, so Hassanpour proposed the field excavation index model (FPI) [8].

Due to the actual geological situation is often a lot of uncertainty, conventional survey methods have some limitations on the parameters of surrounding rock, and most of the existing models use the measured data, do not consider the randomness of input data; the other hand, taking into account the practicality of the model, the selected parameters to be more applicable to the corresponding standard system, to minimize the human factors and the machine itself caused by differences in errors, pay attention to ease of use [9].

So wedo a series of fitting forecasts from the actual mining process easy to collect the data, the final proposed model satisfies high accuracy and short time algorithm, which provides the basisfor the next machine management work.

Basic principle

RBF neural network

(1) In this paper, we use the basis function is the Gaussian function, RBF is a three-layer forward network with a single hidden layer [10], the first layer is the input layer. The hidden function of the neurons in the hidden layer (radial basis function) is a nonnegative linear function that is radially symmetric and attenuating the center point, and the hidden function of the neuron in the hidden layer is defined as the hidden layer. The function is a local response function, the specific local response is reflected in the visible layer to the hidden layer of the transformation with other networks.

The third layer is the output layer, which is the response to the input pattern, which is usually characterized by a simple linear function. RBFNN is a local approximation function [11],the network topology is shown below.

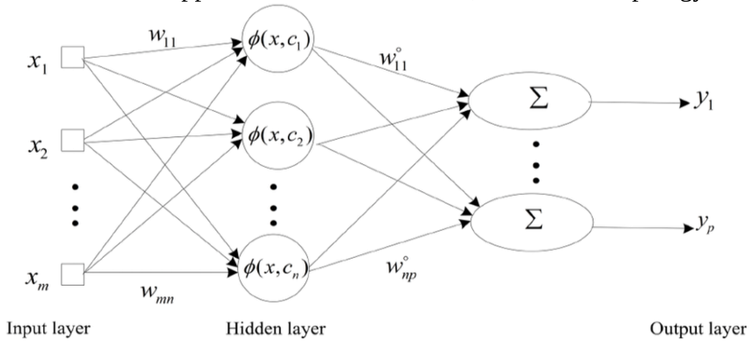

Fig.1 Topological Structure of Radial Basis Function

The Gaussian function of the hidden layer is expressed as:

$$\phi(x,c_i) = \exp\left[\frac{-\left\|X - c_i\right\|^2}{2\sigma_i^2}\right] \quad i = 1,2,\cdots n \tag{1}$$

Where, $\phi(x,c_i)$ represents the output of the $i\text{-}th$ hidden node, X indicates the input sample $X = (x_1, x_2 \cdots x_n)^T$, c_i represents the center of the Gaussian kernel function of the $i\text{-}th$ hidden node and has the same dimension as X, σ_i represents the $i\text{-}th$ hidden layer node variable, called the normalization coefficient (base width); m represents the number of hidden layer.

(2) For the radial basis function network learning algorithm we choose the commonly used K-NN algorithm. K-NN algorithm first clustering the training samples of the independent variable space, dividing the number of classes as the number of nodes of the hidden layer, the centers of the various types are centered on the radial basis function,the variance of each class is transformed into a width parameter. θ_i represents all samples of $i\text{-}th$ group, so there is the following relationship.

$c_i = \frac{1}{M_i}\sum_{x\in\theta_i} X \quad \sigma_i^2 = \frac{1}{M_i}\sum_{x\in\theta_i}(X - c_i)^T(X - c_i)$, Where M_i represents the number of samples for $i\text{-}th$ group.

Adaptive floating point coding genetic algorithm

Genetic algorithm is an adaptive heuristic global search algorithm that simulates biological evolution [12], its essence is copy - crossover - mutation - choose 4 process cycles.Floating-point coding is basically the same as binary coding, and the main differences are reflected in hybridization and mutation operations. The location of the floating-point code exchange can only be selected at the interval of the individual vector element (floating point), which can only have $q-1$ exchangeable positions, and the binary code exchange position operation can choose $p \in \{1, L-1\}$, where L is the length of the binary code string and q is the number of variables to be searched.The mutation method is an element of the vector selected by the mutation probability, variant elements of a_x variation of the results $a_x' = v_x + (u_x - v_x)\times r$, where, v_x, u_x denote the left and right borders of the elements, respectively.

The adaptive characteristics are the change of probability and mutation probability, the expressions for P_c and P_m in AGA are:

$$P_c = \begin{cases} k_1(f_{\max} - f')/(f_{\max} - f_{avg}) & if \quad f' > f_{avg} \\ k_3 & if \quad f' < f_{avg} \end{cases} \qquad (2)$$

$$P_c = \begin{cases} k_2(f_{\max} - f')/(f_{\max} - f_{avg}) & if \quad f > f_{avg} \\ k_4 & if \quad f < f_{avg} \end{cases} \qquad (3)$$

Where, $f_{\max}$ is the maximum fitness of the population, f_{avg} is the average fitness of the population, f' is the larger of the two strings in the exchange, and f is the fitness value of the variant individual.

3 Establish forecasting modelbased on improved genetic algorithm—radial basis function networks

In order to achieve the goal of improving the progress of mining, we choose to optimize the excavation machine, hoping to know in advance the next work area tool wear, achieving early detection of the problem, ahead of schedule a new replacement time, thus arranging new replacement times in advance. In this paper, we analyze the mainstream of the generic shield machine, according to the angle, shape, location of the blade is divided into four groups. The data are composed of four different groups of training, simulation, and construct a reasonable forecasting model.

(1) The choice of indicators

According to experience, the factors that affect the wear are rock grade, rock texture, groundwater, rock uniaxial compressive strength, mileage, cutter speed, shield machine usage, cutter head thrust, radius, torque, tool damage, wear coefficient, blade angle and so on. Some are easy to measure and some are difficult to obtain. The first step is to filter the variables firstly, and there are some collinearity, such as (thrust and torque, wear coefficient and rock grade).

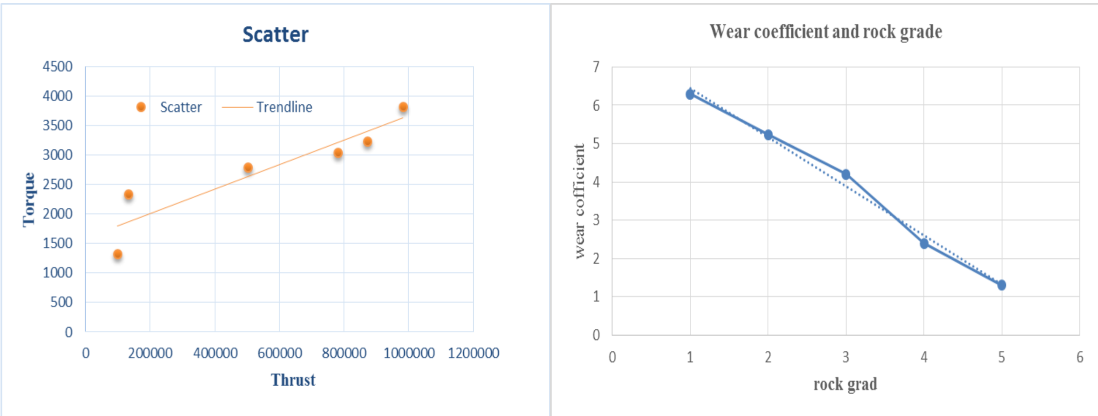

Fig.2 Variable trends and relationships between variables

According to the trend of each variable, we synthesize the results of principal component analysis and data collection. Finally, seven variables were selected as our indicators to participate in the subsequent modeling calculations.

(2) Data preprocessing

The processing of the original data is mainly from the integrity and accuracy of the two aspects to audit.The missing data is compensated by the difference method or the mean method. For obvious anomaly data, we use the delete method to directly remove the data from the interference. For the existence of units of data is not unified, we choose to use standardized methods.

(3) Establish the forecasting model

This paper first realizes the real number of digital strings in AGA, by using a decimal string to replace a binary string to characterize the parameters, avoiding the problem that the range of the network is ambiguous. The basic idea of the model is that the number of nodes of the hidden layer, the center parameter c_i and the width parameter σ_i of each hidden node are coded into chromosomes in the AGA, the collection of these parameters in the network is used as an individual, in the initialization phase to produce a large number of individuals - groups.

The network structure optimization and parameter learning are divided into two stages. First, randomly generating N individuals and they are composed of a groups, and then using the gradient descent method to learn the number of hidden nodes in each individual chromosome corresponding to the center of the network c_i and the width of the parameters σ_i, and then use the least squares method to learn the linear weight of the network w_i, then the genetic algorithm is used to optimize the number of hidden nodes. Through the alternation of these two processes, the BRF network with different basis parameters is obtained. The model is divided into the following steps:

(I). Randomly generating sets the network parameters in different real numbers of N number of groups U^T, corresponding center parameters c_i and width parameters σ_i, which is a population. The value of U^T is 0 or 1, supposing the most optimal individual is the first individual and the optimal fitness is $f_{old\text{-}\max} = -150$.

(II). Using the gradient descent method to initialize the parameters of training and the implementation of a limited number of times. And then use the least squares learning network of linear weights w_i, while calculating the fitness of each population f , and the hidden nodes that do not satisfy the condition are deleted (the constraint condition of the feasible domain is: when $u_i = 1$, corresponding to the weight of $w_i < \sigma$ hidden node, is σ the default value), repeat this operation until all nodes are viable domain nodes, and if the new zeroes appear, the individual is regenerated.

(III). Let $f_{new-\max}$ is the maximum value of the fitness function in the population, contrast with the next individual, if $f_{new-\max} > f_{old-\max}$ can be established, so $f_{old-\max} = f_{new-\max}$, the result isthat the individual corresponding to $f_{new-\max}$ is retained; if $f_{new-\max} < f_{old-\max}$, so $f_{old-\min} = f_{new-\max}$, he result isthat the individual corresponding to $f_{new-\max}$ is retained.

(IV).Whenthe number of hidden nodes (the number of 1) is the same, such as more than 95% in the majority of individuals in the population, then the same number of hidden layer nodes is counted as m , if we can select the most adaptive individuals, going to step (6), otherwise going to step (5).

(v) For the weights of the N group, the individual is selected, crossed and mutated according to the previous formulas (2) and (3).For the exchange, we use single point exchange, U_c^T and U_σ^T are changed synchronously; for the mutation operation, the individual U^T makes the mutation after the probability P_m exchange. The center of the network c_i and the width of the parameters σ_i are changed synchronously, and converting to step (2). The individuals who respond to the greatest fitness are continually performing the gradient descent method several times. Until the accuracy requirements are met. Through detailed step decomposition, we established a complete wear prediction model and established a model based on multiple sets of tools.

4 Simulation and verification

According to the model established in front of the paper, we randomly selected the line 3 from 10 single lines, using its data to test the validity of the model. First of all, the data on the third line is used do the pretreatment, the following is the simulation results of the No. 5 tool.

Table. 1 The actual wear and the amount of wear of the No.5 tool

Date	1	2	3	4	5	6	7	8	9	10	11
Real Wear	1.32	3.55	5.33	8.23	8.88	9.14	10.53	14.24	15.24	18.42	24.23
Forecast	1.42	3.66	5.23	8.43	8.53	9.33	10.6	14.33	15.21	17.33	23.99

Wear											
Error	7.5%	3.1%	1.9%	2.4%	3.9%	2.1%	0.6%	0.6%	0.2%	5.9%	0.9%

From the table we see that the average error of the prediction of the tool 5 is 2.7%, the accuracy rate can meet the requirements. Learning training is carried out after42 knives are divided into four groups, the average error of each group also meet the requirements. The results are shown below.

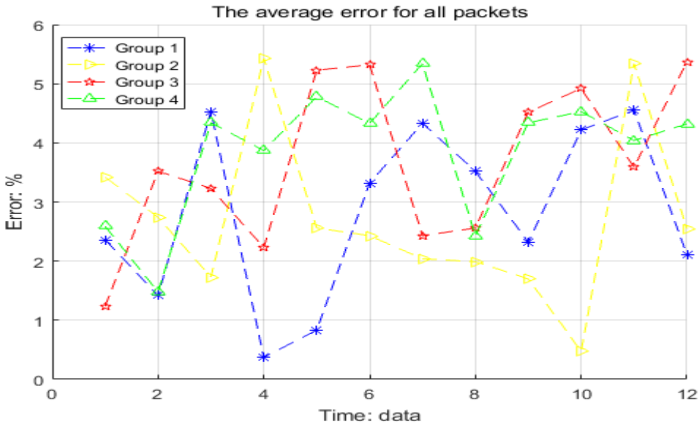

Fig.3 The average error of each group

According to the data in the figure, the average error for each group is 2.823%, 2.7%, 3.68%, and 3.82% respectively. The overall error is controlled within 4%. In order to test the robustness of the structure, we conducted a number of sets of learning and training, in the number of hidden layer 8 under the premise, the average error of multiple results is less than 5%.Finally, our algorithm and radial basis function learning algorithm to do the speed of contrast, the results show that the average time is faster 2.86s after the introduction of genetic algorithm, and the speed is increased by 37%, which indicating that our model is efficient.

CONCLUSION

In this paper, in view of the reality of the optimization problems, in order to optimize the management, shorten the duration become our a starting point, we choose to predict the amount of tool wear in advance for the follow-up of the transport and stocking do theoretical research.

From the simplicity and reliability, the data is used as the input layer, the final establishment of a stable prediction model is completed after several training and training. The prediction model realizes the accurate mapping between the data, sensitivity is reduced and is important for practical operation. The final experimental results show that the average error rate of the new algorithm is 4.57%, and the learning time is obviously shortened by 37%. It is proved that our algorithm is effective to predict the wear amount, which can improve the working efficiency of the machine and save a lot of cost.

REFERENCES

1. Rostami J, Ozdemir L. A new model for performance prediction of hard rock TBMs[C]//Proceedings of the rapid excavation and tunneling conference. Society For Mining, Metallogy & Exploration, INC, 1993: 793-793.
2. Rostami J. Development of a force estimation model for rock fragmentation with disc cutters through theoretical modeling and physical measurement of crushed zone pressure[D]. Colorado School of Mines, 1997.
3. Bruland A. Hard rock tunnel boring[D]. Fakultet for ingeniørvitenskapogteknologi, 2000.
4. Blindheim O T. Boreability predictions for tunneling[J]. Trondheim, Norway: The Norwegian Institute of Technology, 1979.
5. Sapigni M, Berti M, Bethaz E, et al. TBM performance estimation using rock mass classifications[J]. International Journal of Rock Mechanics and Mining Sciences, 2002, 39(6): 771-788.
6. Barton N R. TBM tunnelling in jointed and faulted rock[M]. CRC Press, 2000.
7. Gong Q M, Zhao J. Development of a rock mass characteristics model for TBM penetration rate prediction[J]. International journal of Rock mechanics and mining sciences, 2009, 46(1): 8-18.

8. Hassanpour J, Rostami J, Zhao J. A new hard rock TBM performance prediction model for project planning[J]. Tunnelling and Underground Space Technology, 2011, 26(5): 595-603.
9. Tatsuhama T, Okabe M. Method of and apparatus for determining angular and transversal displacements of shield machine and succeeding pipe: U.S. Patent 4,392,744[P]. 1983-7-12.
10. Yingwei L, Sundararajan N, Saratchandran P. Performance evaluation of a sequential minimal radial basis function (RBF) neural network learning algorithm[J]. IEEE Transactions on neural networks, 1998, 9(2): 308-318.
11. Gharagheizi F. QSPR analysis for intrinsic viscosity of polymer solutions by means of GA-MLR and RBFNN[J]. Computational materials science, 2007, 40(1): 159-167.
12. Whitley D. A genetic algorithm tutorial[J]. Statistics and computing, 1994, 4(2): 65-85.