Identification on rock and soil parameters for vibro-cutting rock by disc cutter based on fuzzy radial basis function neural network

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Abstract: A single-POF model of disc cutter with rock and soil has been established according to the dynamical feature and vibration mechanism of disc cutter vibro-cutting rock to solve problem of self-adaption vibro-cutting rock for disc cutter, and identification on rock and soil parameter of disc cutter vibro-cutting rock has been carried out by using fuzzy radial basis function neural network. The experimental result of identification simulation and resonant-column test showed that compared to inherent frequency of a hard sandy which was tested by resonant-column test method, the relevant error of rock and soil parameter identification value of disc cutter vibro-cutting rock is 0.87 %, with high estimation accuracy.

1 Introduction

Characteristics of large-scale, automation, high speed, processize, and delicate are combined into one full face hard rock tunnel boring machine[1-3], it is wildly used in tunnelings[4-6]. Disc cutter is the main cutter of TBM vibro-cutting rock, the excavation schedule of tunnelings and lifetime of cutters could be direct influenced by its efficiency of breaking rock[7]. Therefore, it was regarded as the significant problem for domestics and overseas specialists to research on improving the breaking rock efficiency of cutters and extending service life of cutters.

With the development of the vibration technology and artificial intelligence technology[8], as a kind of energy-efficient advanced technology, vibro-cutting has been successful applied in several fields like rock breakage and rock excavation at present[9]. Vibro-cutting was put into coal-cutting exploratory experimental research by researchers as early as 1980s, experimental research of cutting- lignite using single-tooth to simulate vibration is showed in document[10]. Single-tool tooth and coal sample was used to simulate the cutting process of reality coal cutting in the situation of relative vibration in document [11], and similarity theory was used to build up the experimental model, then orthogonal experimentation was also used to carry out optimal experiment aimed at this model to search for obviously depressed parameter combination of cutting force and unit energy consumption. In rock breakage experimental research side of vibro-cutting, the result of vibro-cutting tuff was showed in document [12] that the ratio of horizontal cutting resistance in vibration and horizontal cutting

resistance without vibration has been rapidly decreased hyperbolic along with the vibrational frequency has been increased, and the cutting efficiency of since wave vibration is higher than the cutting efficiency of triangular wave vibration. A super-frequency vibration tester aimed at going deeply into the performance of vibro-cutting was developed in document [13], and the measured cutting moment, main cutting force, vertical cutting force in vibrational state are showed that they are smaller than those in no vibrational state when we change the vibrate frequency and cutting angle of cutters, and if the inherent frequency of the cut material is closed to vibrational frequency, the cutting state will be stable and high efficiency. Vibration caused by ultrasonic of 10kHz and 10kW on rock-boring and rock-cutting was applied in document [14], the results shown that the needed energy of cutting rock is decided by the tool shape, static-pressure, angle of cutting edge and so on.

Some conclusions can be gotten from above researches as follows. If disc cutter self-adaptation vibro-cutting rock is realized, that is to say, process of vibro-cutting rock can be automatically adjusted to different vibration parameter such as frequency, amplitude and input waveform according to different rock condition parameter including its inherent frequency and damping ratio, the rock condition parameters must be identified rapidly[15]. And special advantages of fuzzy radial basis function neural network method is useful for solving such kind of problem, based on building a single-POF model of disc cutter with rock and soil, identification on rock and soil parameter of disc cutter vibro-cutting rock has been carried out in this paper by using fuzzy radial basis function neural network. This research result has important theoretical significance and reference value in realizing disc cutter self-adaption

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vibro-cutting rock.

2 Rock and soil parameter model of disc cutter vibro-cutting rock

2.1 Disc cutter rock breaking mechanism

Figure 1 is a simple structure diagram of disc cutter. Disc cutter is consisted of cutter body, cutter ring, check ring, bearing, seal ring and so on. An enormous influence was made by cross-section shape of cutter ring on rock

breaking efficiency, the bigger external diameter of the cutter ring is, the bigger breaking square will be, the diameter of cutter is up to 500mm at present, contour line of cutter ring has been developed from wedge-shape to streamline nowadays, with a normal circular arc radius of 4mm, and thickness of cutter ring is in different from 57.2mm to 80mm according to different cutter type and formation factor. Hot work die steel is taken as principle thing for material of cutter ring, with a bigger impulse and load can be undertaken by its high hardness, and a better wear-resisting property is owned.

1-cutter body; 2-check ring; 3-cutter ring; 4-bearing; 5-seal ring; 6-end cover; 7-cutter shaft

Figure 1 Simple structure diagram of disc cutter

Disc cutter is rolled on the excavation surface at tunneling piercing process because of the rubbing action, when the rock intension was exceeded by the acting cutter load, rock will be destroyed, and be away from source rocks. During the rock breakage process of disc cutter, the cutter is suffered applied force from three direction: the first one is vertical force (radial force of cutter ring), it means the needed impulse force when disc cutter is breaking rocks, and plane of tunnel face is perpendicular to the needed impulse force; the second one is rolling force, it means the needed twisting force of disc cutter is actuated by cutter rolling on rocks, it's on the tunnel face plane and is tangent to the move rotundity

of cutter; the third one is yawing force, it means the suffered unbalance loading when disc cutter breaking rock, it is parallel to tunnel face and cutter shaft axes of disc cutter. When BM disc cutter is breaking rocks, rocks are invaded into disc cutter at first, and then heavily stressed crushing area and radial crack are formed at the underface direction of cutter blade, it is showed in Figure 2. Then, hob is driven by cutter to cut rock tunnel face, the invalidation area of blade is expanded and the inner crack of rock is made to expand around and to deeply area, when crack and free surface are met or the crack between hobs threaded together, massive rock dregs appeared.

Figure 2 Rock breakage system under the action of single-hob

2.2 Establishment of the rock and soil parameter model of disc cutter breaking rock

The process of disc cutter breaking rock is interaction schematic diagram of rock and soil with drill. According to dynamical features and vibration mechanism of disc cutter breaking rock, cutter is whirling vibrated to break rocks under the effect of ultrasonic, it is showed in Figure 3 that a single-DOF system is consisted of disc cutter and rock and soil, m_1 is represented as the mass of cutter ring segment closed to the driving face, kg; m_2 is represented as sum of the cutter body and cutter ring removing the mass of m_1 , bearing outer ring, and half mass of bearing roller, kg; m_3 is represented as the sum of half mass of bearing roller, the inner race of bearing mass and half mass of bearing, kg; k is the equivalent spring stiffness of rock and soil, N/m; c is equivalent damping coefficient of rock and soil.

Figure3 single-POF model of disc cutter with rock and soil

Single-POF system of disc cutter with rock and soil is a single-DOF system which exciting force $F(\tau)$ is used as input, and displacement z is used as output, and its differential equation is :

$$m \frac{d^2 z}{d\tau^2} + c \frac{dz}{d\tau} + kz = F(\tau) \quad (1)$$

Where, τ is the time, s; $m = m_1 + m_2 + m_3$.

Sample is taken for Single-POF system of disc cutter with rock and soil in a very small sampling period τ_0 , then we have:

$$\left. \frac{dz}{d\tau} \right|_{n\tau_0} = \frac{z(n\tau_0) - z(n\tau_0 - 1)}{\tau_0} \quad (2)$$

$$\left. \frac{d^2 z}{d\tau^2} \right|_{n\tau} = \frac{d}{d\tau} \left(\frac{dz}{d\tau} \right) = \frac{z(n\tau_0) - 2z(n\tau_0 - 1) + z(n\tau_0 - 2)}{\tau_0^2} \quad (3)$$

Put formula (2) and (3) into formula (1), get:

$$\begin{aligned} & \left(\frac{m}{\tau_0^2} + \frac{c}{\tau_0} + k \right) z(n\tau_0) - \left(\frac{2m}{\tau_0^2} + \frac{c}{T} \right) z(n\tau_0 - 1) \\ & + \frac{m}{\tau_0^2} z(n\tau_0 - 2) = F(n\tau_0) \end{aligned} \quad (4)$$

Let

$$\alpha = -\frac{2m/\tau_0^2 + c/\tau_0}{m/\tau_0^2 + c/\tau_0 + k}, \quad \beta = \frac{m/\tau_0^2}{m/\tau_0^2 + c/\tau_0 + k},$$

$$\varepsilon = \frac{1}{m/\tau_0^2 + c/\tau_0 + k}, \tau_0 \text{ of } z(n\tau_0), z(n\tau_0 - 1), z(n\tau_0 - 2) \text{ and}$$

$F(n\tau_0)$ are left in formula (4), so difference equation of single-POF model of disc cutter with rock and soil can be described as:

$$z(n) + \alpha z(n-1) + \beta z(n-2) = \varepsilon F(n) \quad (5)$$

where parameter α , β , ε is relevant to the sampling period τ_0 .

If we can get the value of α , β , ε through identification, so rock and soil parameter of disc cutter breaking rock can be expressed as:

$$m = \frac{\beta}{\varepsilon} \tau_0^2, c = -\frac{\alpha + 2\beta}{\varepsilon} \tau_0, k = \frac{1 + \alpha + \beta}{\varepsilon}$$

(6)

Resonance inherent frequency f_y of rock and soil during process of disc cutter vibrating breaking rock can be expressed as:

$$f_y = \sqrt{\frac{1 + \alpha + \beta}{\beta}} \frac{1}{2\pi\tau_0} \quad (7)$$

In the rock and soil parameter identification of disc cutter vibro-cutting rock, all conversion of random factors can be converted into output terminal to centralize into noise $\psi(n)$, showed in Figure 4.

Figure 4 single-POF random model of disc cutter with rock and soil

Then, the model is:

$$z(n) + \alpha z(n-1) + \beta z(n-2) = \varepsilon F(n) + \psi(n) \quad (8)$$

After signal based on wavelet analysis is used to do the de-noise processing, formula (8) can be simplified as the model showed in formula (5) above.

3 Rock and soil parameter identification model of disc cutter vibro-cutting rocks based on FRBF-NN

3.1 Identification of FRBF-NN

FRBF-NN model is which not only is similar to feedforward network, but also is a network structure which can accurate reflect fuzzy logical rule of inference, it is showed in Figure 5.

Figure 5 Neural network structure of FRBF

Because of fuzzy inference rule is used to construct feed-forward spread structure, so model structure FRBF-NN showed in Figure 5 is more optimizing and transparent, and the inferential capability is further improved.

This FRBF-NN is consisted of layers including input layer, fuzzification layer, regulation layer, normalization layer, and output layer. Because of RBF network is used so that the connection between each layer is linear connection through the first layer to the fourth layer. All the connection weight is one; the connection weight from normalization layer to output layer is adjustable.

Suppose there are n input variable, including $x_1, x_2, \dots, x_n$, and r output variable, including $y_1, y_2, \dots, y_r$.

The first layer is input layer. Each node is directly connected with each component of output vector, n is the input dimension.

The second layer is fuzzification layer. Each node is represented as one linguistic variable value, Gaussian function is used as fuzzy subordinating degree function to obscure input variable:

$$\mu_{ij} = \exp\left[-\left(\frac{x_i - c_{ij}}{\sigma_{ij}}\right)^2\right] \quad (9)$$

where μ_{ij} is subordinating degree function of the i^{th} input variable which belongs to the j^{th} linguistic variable, $i=1,2,\dots,n, j=1,2,\dots,r$; c_{ij} is central value of membership function μ_{ij} , σ_{ij} is width value of membership function μ_{ij} .

The third layer is regulation layer. Each node is represented as one fuzzy rule used to match precondition of fuzzy rule, logical multiplication is used to calculate adaptability of each rule:

$$\alpha_j = \mu_1^{i1} \mu_2^{i2} \dots \mu_n^{in} \quad j = 1, 2, \dots, m \quad (10)$$

$$m = \prod_i m_i \quad (11)$$

where m is the fuzzy rule number in this model.

The fourth layer is normalization layer. The normalization calculation is realized below:

$$\bar{\alpha}_j = \alpha_j / \sum_{j=1}^m \alpha_j \quad (12)$$

The fifth layer is output layer. Central average sharpness calculation is realized below:

$$y_i = \sum_{j=1}^m w_{ij} \bar{\alpha}_j \quad i = 1, 2, \dots, r \quad (13)$$

where w_{ij} is the connection width of neural network, and is equivalent to the j^{th} linguistic values membership function central value of y as well.

The conventional learning algorithm of FRBF-NN is improved, and the improved specific process of FRBF-NN learning algorithm is showed below:

Step1: clustering center c_{ij} is initialized $i=1,2,\dots,N_r$;

Step2: all the fuzzy input variables are divided into different groups through rule of nearest cluster center, if:

$$\|\mu_{ij} - c_{ij}\| = \min_{j \in N_r} \|\mu_{ij} - c_{ij}\| \quad (14)$$

Then, μ_{ij} is assigned to θ_j , θ_j is represented as the collection of training patterns around clustering center c_{ij} .

Step3: clustering center is recounted:

$$c_{ij} = \frac{1}{M_j} \sum_{x_i \in \theta_j} \mu_{ij} \quad (15)$$

where, M_j is the element amount of θ_j .

Step4: step2 and step3 are repeated until clustering center c_{ij} is no longer changing.

Step5: the width between middle tier and output layer is initialized. And smaller random number is used to assign weight w_{ij} .

Step6: the width value of σ_{ij} membership function μ_{ij} is confirmed. It is represented as one measurable of data scatter with the relationship of each center, and it can be ensured through several ways. This paper order σ_{ij} is equal to average distance between cluster center and training pattern:

$$\sigma_{ij}^2 = \frac{1}{M_j} \sum_{x_i \in \theta_j} (\mu_{ij} - c_{ij})^T (\mu_{ij} - c_{ij}) \quad (16)$$

Step7: the width is updated. After the primary function parameter is confirmed, we should update width under formula (17):

$$w_{ij}(t+1) = w_{ij}(t) + \eta(y_{di} - y_i) \bar{\alpha}_j \mu_{ij} \quad (17)$$

where, η is learning rate, $\eta=1-[(t+1)/t]^2$; y_d and y are desired output and actual output of training sample respectively.

Step8: judge the termination conditions. Define error function MSE as generalization performance evaluation index of neural network FRBF:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_{di} - y_i)^2 \quad (18)$$

If the value of MSE is less than 1.0×10^{-4} , then termination condition will be satisfied and end up. Otherwise, go back to step6.

3.2 Realization of the rock and soil parameter identification of disc cutter vibro-cutting rock

Single-DOF discrete linear system of disc cutter with rock and soil can be represented by normally difference equation after using signal based on wavelet analysis to do the de-noise processing.

$$y(n) = -\alpha y(n-1) - \beta y(n-2) + \varepsilon F(n) \quad (19)$$

Rock and soil parameter identification of disc cutter vibro-cutting rock is a math model which method of FLS-SVM is used to identify objects through the changing data series of input and output of disc cutter

with rock and soil single-DOF system, that is to say, $y(n-1), y(n-2)$ and $F(n)$ are used as input training vector quantity of FLS-SVM, and $\{x_1, x_2, x_3\}, y(n)$ as the output training vector quantity of FLS-SVM to make output of identification model $y(n)$ and output of the identified model $y'(n)$ come near as much as possible, the same as to try to make the difference between $y(n)$ and $y'(n)$ become smaller.

3.2.1 Self-adaption genetic algorithm optimize parameter of FRBF-NN

For parameter of FRBF-NN, whether central value of membership function and width value of membership function are optimized will make influence on the precision of rock and soil parameter identification of disc cutter vibro-cutting rock to a great extent. Therefore, self-adaption genetic algorithm is adopted to optimize parameter of FRBF-NN.

$$F(c_{ij}, \sigma_{ij}) = \frac{1}{\sum_{i=1}^n [y_i - f(x_i)]^2 + e} \quad (20)$$

where y_i is desired output, $f(x_i)$ is realistic output, e is a very small positive number, with an effect of preventing to occur situation of denominator is zero.

And error function MSE is identified as evaluation index of FRBF-NN generalization performance [18].

$$MSE = \frac{1}{M} \sum_{i=1}^m [f(x_i) - y_i]^2 \quad (21)$$

where y_i is desired output, $f(x_i)$ is realistic output.

Initial crossover probability and initial mutation probability can be represented by formula (22) and formula (23):

$$P_c^1 = \begin{cases} 0.95 - 0.35(f_1 - f_{avg}) / (f_{max} - f_{avg}), & f \geq f_{avg} \\ 0.95, & \text{else} \end{cases} \quad (22)$$

$$P_m^1 = \begin{cases} 0.15 - 0.09(f_{max} - f) / (f_{max} - f_{avg}), & f \geq f_{avg} \\ 0.15, & \text{else} \end{cases} \quad (23)$$

Where, f_1 is fitness function of crossing two bigger size, f is size of fitness function corresponding to unit, is the average fitness of sample, and is the maximum fitness of sample unit. Crossover probability and mutation probability is changing following the generation of evolution, its rule is showed below:

$$P_c^t = \begin{cases} 0.8 \times \sqrt{1 - (t/t_{max})^2} & P_c^t < 0.5 \\ 0.5 & \text{else} \end{cases} \quad (24)$$

$$P_m^t = \begin{cases} 0.05 \times e^{(-\lambda \cdot t / t_{max})} & P_m^t < 0.0005 \\ 0.0005 & \text{else} \end{cases} \quad (25)$$

where t is the genetic algebra, and t_{max} is terminal algebra, λ is constant, here we should choose ten in this formula.

Value range of width value of membership function μ_{ij} is [0.05, 0.95], value range of clustering center is [0.05, 0.95], the population amount of self-adaption genetic optimization procedure is set to be $N_{ind}=30$, the preparative optimizing parameter amount, also, the variable dimensionality is $N_{var}=3$; the maximum genetic algebra is set to be $M_{axgen}=350$; the binary system digit of each variable is set to be $P_{reci}=20$. The initial variable is initialed, also is to assign zero or one to $30 \times 3 \times 20$ binary code

3.2.2 Simulation for the rock and soil parameter identification of disc cutter vibro-cutting rock

According to the realistic breaking rocks process situation of disc cutter vibro-cutting rock, a group typical data of hard sand soil is gotten: $\alpha = -2.758 \times 10^{-7}$, $\beta = 4.412 \times 10^{-9}$, $\varepsilon = 2.698 \times 10^{-7}$ and $F(n) = 62.5\pi \cos(4 \times 10^4 \pi n)$, $y(n-1)$, $y(n-2)$ and $F(n)$ are used as input training vector quantity for FRBF-NN, and $y(n)$ is output training vector quantity for FRBF-NN. Such sample Dataset is gotten below: (1) four hundred sample are gotten, and half of it is training sample, the others is testing sample. (2) three hundred sample are gotten, half of it is training sample, the others is testing sample.

Figure 6 is the error corresponding to thirty population units after optimizing iterate 200 steps of self-adaption genetic algorithm, the average error is 0.0983, for the process of Simulation for the rock and soil parameter identification of disc cutter vibro-cutting rock which have 150 training and testing sample, and the average error is 0.0860 for the process of Simulation for the rock and soil parameter identification of disc cutter vibro-cutting rock which have 200 training and testing sample.

Figure 7 is the error which correspond to thirty population units after optimizing iterate 350 steps of self-adaption genetic algorithm, the average error is 0.005357, for the process of Simulation for the rock and soil parameter identification of disc cutter vibro-cutting rock which have 150 training and testing sample, the minimum error is about 0.0024. And the average error is 0.00519 for the process of Simulation for the rock and soil parameter identification of disc cutter vibro-cutting rock which have 200 training and testing sample, the minimum error is about 0.0014.

(a) 200 training sample, 200 testing sample

(b) 250 training sample, 150 testing sample

Figure 6 Error of species after 200 steps

(a) 200 training sample, 200 testing sample

(b) 250 training sample, 150 testing sample

Figure 7 Error of species after 350 steps

The testing error of the rock and soil identification parameter model of disc cutter vibro-cutting rock is showed in Figure8. The generalization ability of FRBF-NN is very strong, for the process 200 testing sample and 200 training sample are contained, the gotten maximum testing error is 0.13mm (relevant error at this time is 1.01%), and for the process 150 testing sample

and 150 training sample are contained, the gotten maximum testing error is -0.15mm (relevant error at this time is -1.11%). Conclusion could be gotten that too much data sample earns not obviously for rock and soil identify parameter model of disc cutter vibro-cutting rock based on FRBF-NN.

(a) 200 training sample, 200 testing sample

(b) 150 training sample, 150 testing sample

Figure 8 Error curve of measurement sets

Least Square Support Vector Machines, LS-SVM, FRBF-NN, Fuzzy Neural network, FNN are used to identify for rock and soil parameter of disc cutter

vibro-cutting rock respectively, and the gotten result showed in the table below:

Table 1 Comparison of identification results on rock and soil parameter for vibratory drilling rock in the metal mine

Sample amount	150 for training set and testing set			200 for training set and testing set		
index	α	β	ε	α	β	ε
Original system	-0.1276	0.4187	6.82×10^{-7}	-0.1276	0.4187	6.82×10^{-7}
LS-SVM	-0.1258	0.4162	6.62×10^{-7}	-0.1264	0.4170	6.71×10^{-7}
FRBF-NN	-0.1270	0.4181	6.74×10^{-7}	-0.1273	0.4186	6.81×10^{-7}
FNN	-0.1265	0.4167	6.66×10^{-7}	-0.1268	0.4179	6.77×10^{-7}

Form the Table 1, it is seen that when training set and testing set are both 150, there are larger difference between the identified parameter of LS-SVM with FNN and parameter of original system, and when training set and testing set are both 200, identified parameter accuracy of LS-SVM and FNN are improved a lot; The gotten parameter of FRBF-NN is closed to system parameter with little change when the sample of testing set and training set are both 150, that is to say FRBF-NN identification has smaller identify error and better identify ability than LS-SVM and FNN identification so that it will be more fitness for the identification of dynamical system.

On-line identification method of disc cutter vibratory drilling rock inherent frequency parameter based on FRBF-NN is used to identify parameter of the rock breakage process for hard sandy soil: $\alpha=-0.127$, $\beta=0.4186$, $\varepsilon=6.81 \times 10^{-7}$, so $k=1.8932 \times 10^6 \text{ kN/m}$, $m=m_1+m_2+m_3=2.444+76.051+38.55=117.045 \text{ kg}$, the inherent frequency of such hard sandy soil is gotten to be $f=40.4828 \text{ Hz}$. Resonant-column test method is used to get the inherent frequency of such hard sandy soil $f=40.84 \text{ Hz}$.

The rock and soil inherent frequency parameter identification value of breaking rocks based on FRBF-NN is very closed to the tested inherent frequency of such hard sandy soil, and the error is 0.87%. High precision is owned by rock and soil parameter identification result of vibratory drilling rock.

4 Conclusions

(1)Self-adaption genetic algorithm optimize penalty factor and kernel parameter is used to identify the built parameter of single-DOF model of disc cutter with rock and soil, realizing rock and soil parameter identification of disc cutter vibro-cutting rock for FRBF-NN. The simulation result is showed that the maximum error for rock and soil parameter identification of disc cutter vibro-cutting rock for FRBF-NN is 1.11%.

(2)Compared to the tested inherent frequency of such hard sandy soil by resonant-column test, the relevant error of rock and soil parameter identification of disc cutter vibro-cutting rock based on FRBF-NN is 0.87%, it is showed that rock and soil parameter identification result

of disc cutter vibro-cutting rock has a high precision.

5 Conflict of Interests

The authors declare that they have no conflict of interests regarding the publication of this paper.

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