Journal of Basic & Applied Sciences, 2022, *18*, 65-71

Published by SET Publisher

Journal of Basic & Applied Sciences

ISSN (online): 1927-5129

Prediction of Surface Roughness of U71Mn Steel Milling Based on RBF Neural Network

Zhuang Shudong, Yu Hang, Liu Xiyu* and Jenny Sama Kevin

College of Mechanical and Electrical Engineering, Hohai University, Changzhou 213022, China

Article Info:

Keywords:
U71Mn high manganese steel,
orthogonal test,
Surface Roughness,
RBF Neural Network.

Timeline:
Received: September 09, 2022
Accepted: October 14, 2022
Published: April 17, 2022

Citation: Shudong Z, Hang Y, Xiyu L, Kevin JS. Prediction of surface roughness of U71Mn Steel milling based on RBF neural network. J Basic Appl Sci 2022; 18: 65-71.

DOI: https://doi.org/10.29169/1927-5129.2022.18.08

Abstract:

In order to predict the surface roughness of U71Mn high manganese steel before actual milling operation, an orthogonal experiment was designed. Based on the intelligent algorithm of Radial Basis Functions (RBF) neural network, an accurate prediction model of surface roughness is done with MATLAB. By comparing the predicted data of RBF neural network model with the actual measured data, it is proven that the model is accurate and effective.

*Corresponding Author
E-mail: liuxiyu0321@163.com

U71Mn high manganese steel is the most widely used rail material. presently the most advanced rail repair method is to use the rail milling machine for on-line repair and maintenance. The milling process is responsible for removing most of the surplus, and also requires the surface roughness after milling to reach a certain standard value [1]. Because the surface roughness has an important influence on the fatigue strength, contact stiffness, corrosion resistance and coordination of the rail workpiece. Therefore, it is very important to predict the surface roughness according to the processing method and cutting parameters before actual machining.

1. MILLING TEST AND RESEARCH OF U71Mn STEEL

The experiment of milling U71Mn steel was designed to investigate the influence of various milling parameters on the surface roughness of U71Mn steel.

1.1. Workpiece Material and Size

Since most of the current railways use the standard 60kg/m U71Mn high manganese steel alloy, the specifications are shown in Figure **1** below [2]. Therefore, in order to ensure the engineering significance of the research and the accuracy of the test data, the workpiece is directly selected from 5 sections of rails and the size of the milling surface is 150mm×50mm , the height of the whole test workpiece is176mm, as shown in Figure **2** below.

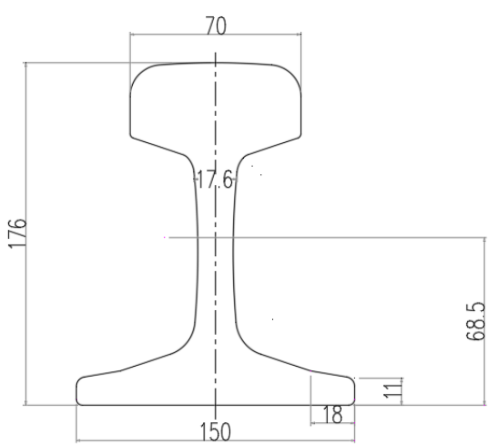

Figure 1: 60 kg/m Standard rail cross-sectional dimensions.

1.2. U71Mn Steel Milling Test Machine Tool

The test machine tool adopts M-V5CN modular machine tool produced by the Japanese Mitsubishi Company as shown in Figure **3** below. Its CNC programming system is also used in FANUC system as shown in Figure **4** below shows the positioning and milling process of the workpiece.

Figure 2: Milling test workpiece.

Figure 3: Mitsubishi M-V5CN modular machine tool.

Figure 4: Milling Workpiece Diagram.

1.3. U71Mn Steel Milling Test Machine Tools and Cutters

For the selection of cutting tools, for work hardening and thermal deformation phenomenon when milling high-manganese steel, the 4 flute carbide flat-bottom end milling cutter with a diameter of 20 mm is adopted here, as shown in Figure **5** below.

Figure 5: Flat-bottom end milling cutter.

1.4. Milling Parameter Design of U71Mn Steel

In order to study the surface roughness and the nonlinear relationship between the spindle speed n, the feed per tooth fz, the milling depth a_p and the milling width ae when milling U71Mn steel. To provide original data for multiple linear regression and a large number of training samples for intelligent algorithm, referring to the manual of cutting parameters and combining with the parameter range of modular machine tools, the range of milling parameters is designed as shown in Table **1** below, which will also be an important constraint for parameter optimization.

Table 1: Factor Level Table

LEVEL	FACTOR			
	n (r/min)	f_z (mm/z)	a_p (mm)	a_e (mm)
1	4000	0.04	1.0	3
2	5000	0.06	1.5	6
3	6000	0.08	2.0	9
4	7000	0.10	2.5	12
5	8000	0.12	3.0	15

Measurement method: The surface roughness of the workpiece after milling was measured by a non-contact photoelectric profilometer. As shown Photoelectric Profilometer Composition instrument in Figure **6** below. Three points are selected uniformly along the radial direction of the cloud image, and the average value is taken as the test result.

2. RBF NEURAL NETWORK DESIGN AND ALGORITHMS

The RBF-Radial Basis Function is a three-layer feedforward network with a single hidden layer that can approximate any continuous function with arbitrary precision. This paper uses this neural network to train the experimental data and establish a model for predicting the surface roughness of U71Mn steel after milling. Its input-output mapping is non-linear, while the mapping from hidden layer to output layer is linear. Because it has the characteristics of local approximation and only one hidden layer, RBF neural network can accelerate learning without local minimal which is suitable for the need of high precision prediction in this subject [3-4].

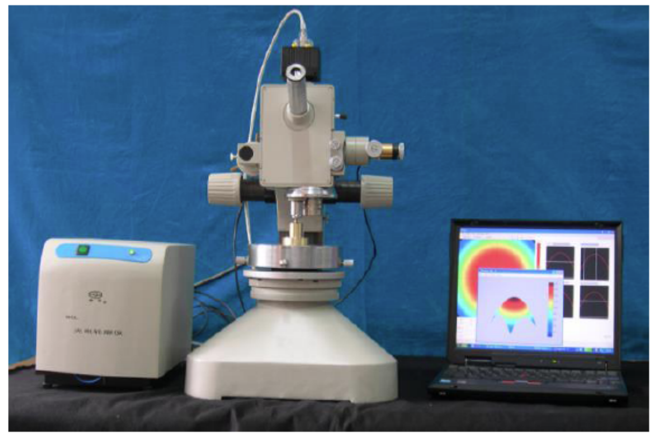

Figure 6: Photoelectric Profilometer Composition Diagram.

2.1. RBF Neural Network Structure Design (Schematic)

Before designing the structure of RBF neural network for predicting the surface roughness of milling U71Mn steel, an important task needs to be completed, that is, the determination of input variables, which can truthfully reflect the change of expected output, and can greatly improve the predictive performance of the network model [5]. Milling U71Mn steel is a complex interrupted cutting process. In this paper, milling parameters are selected as input parameters of neural network, ignoring the influence of machine tool vibration, tool path and cooling mode.

According to the above analysis, the input layer of RBF network is determined to be four inputs. The final research object of this subject is the surface roughness of U71Mn steel after milling, so the output layer is an output, that is Ra value, and the input layer and output layer are designed. As for the hidden layer, the number of neurons and the center of each neuron need to be determined through the training of the algorithm. The structure of the RBF neural network is shown in Figure **7** below.

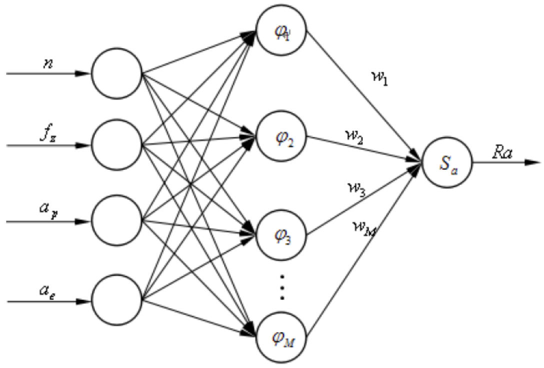

Figure 7: RBF Neural Network Structure for Roughness Prediction.

The first layer is the input layer, which includes spindle speed n, feed per tooth f_z, milling depth a_p and milling width a_e. The second layer is the hidden layer. The Gauss function is used to calculate the non-linear transformation from the input layer to the hidden layer. The output of the third node of the hidden layer is [6]:

$$\phi_i = R(\|x - c_i\|) = \exp\left[-\frac{\|x-c_i\|^2}{2\sigma_i^2}\right], i = 1,2\cdots M \tag{1}$$

In style x——4-Dimensional Input Vector

c_i—— The center of the first basis function,

ϕ_i—— The output of the first node of the hidden layer,

$R(x)$——*RBF basis function*

M—— Number of neurons in the hidden layer,

$\|\bullet\|$——Euclidean norm, representing the space distance between vectors.

The third layer is the output layer, which completes the linear transformation from the hidden layer to the output layer. The output is a linear combination of hidden layer nodes [7]. Combining with the objective of this paper, the output is the roughness value of U71Mn steel after milling, that is:

$$R_a = \sum_{i=1}^{M} w_i \phi_i + \theta \tag{2}$$

Where,

w_i——Connection Weights Between Hidden Layer I Node and Output Layer

θ——*Output node offset*

2.2. RBF Neural Network Learning Algorithm Selection

Taking the four milling parameters of U71Mn steel as input nodes and the measured surface roughness as the expected output of the network output layer, based on the neural network structure and learning algorithm of the prediction model built in the previous section, the RBF network prediction program is written with MATLAB environment. The specific process learning algorithm are as follows:

(1) Find the center point of the RBF function based on K-means clustering Algorithms

a. Network initialization.Choose different vectors as initial clustering centers $c_1(0), c_2(0), \cdots, c_M(0)$。

b. Sample grouping. Follow the principle of minimization x With the Center c_i ,the Euclidean norm between will x allocate to each cluster set Ω_i in them.

c. The adjustment of the center $c_i(k)$ is the center of the first basis function at the first iteration i . The mean is calculated for all cluster sets Ω_i until the data is stable, and the resulting value $k = k+1$ is assigned to the hidden layer. Otherwise, go to the above b.

(2) Solving variance σ_i

variance σ_i can be solved directly by the following formula:

$$\sigma_i = \frac{c_{\max}}{\sqrt{2M}} \quad i = 1,2,\cdots M \tag{3}$$

Where, $c_{\max}$—— Maximum distance between selected centers

M—— Number of Hidden Layer Neurons

M—— Number of neurons in the hidden layer.

After obtaining the center and expansion constants of each radial basis function, the final task is to determine the connection weights between the hidden layer and the output layer. The simplest method is to calculate directly by pseudo-inverse method.

(3) Calculating the weights between the hidden layer and the output layer, When the input is set to zero, the output of the second hidden node is

$$\phi_{pi} = \phi(\|X^p - c_i\|); p = 1,2,\cdots,P; j = 1,2,\cdots,M$$

Then the output matrix of the hidden layer is:

$$\hat{\Phi} = (\phi_{pi})_{p\times M} \tag{4}$$

If the output weight of RBF network is pending then $W = (w_1, w_2, \cdots, w_M)$ Then the network output vector is:

$$F(X) = \hat{\Phi} W \tag{5}$$

Make the network output vector equal to the signal d, then W, available $\hat{\Phi}$ Pseudo-inverse of $\hat{\Phi}^{+}$ is

$$W = \hat{\Phi}^{+} d \tag{6}$$

$$\hat{\Phi}^{+} \left(\hat{\Phi}^{T} \hat{\Phi}\right)^{-1} \hat{\Phi}^{T} \tag{7}$$

The new weights are recalculated, and then the errors are discriminated. If the process is satisfied, the it will stop or the cycle will continue.

3. ESTABLISHMENT OF SURFACE ROUGHNESS PREDICTION MODEL

3.1. Sample Acquisition

According to the orthogonal test designed in the first section, the obtained data was filled in the orthogonal table with25 sets of test results as obtained, as shown in Table **2** below.

3.2. Sample Normalization

A good network model is established and a good learning algorithm is selected. However, the corresponding relationship between input and output can only be determined through a certain degree of training, that is, the non-linear mapping relationship between the four milling parameters of spindle speed, feed per tooth, milling depth, milling width and surface roughness value Ra when milling U71Mn steel. In addition, the unit dimension of milling parameters is different. In order to reduce large decimal errors and improve the process efficiency of neural networks, the data in the table should be mapped to [-1,1] interval. The normalization formula used is:

$$P' = 2(P - P_{\min})/(P_{\max} - P_{\min}) - 1 \tag{8}$$

After prediction, data need to be restored, and the restoring formula is:

$$P = (P' + 1)\cdot(P_{\max} - P_{\min})/2 + P_{\min} \tag{9}$$

Where:

P ——Sample raw data, $P_{\min}$ ——Minimum in Sample , $P_{\max}$ ——Maximum in Sample, P' ——Data after normalized pretreatment

3.3. Analysis and Verification of Training Results

The network model for accurately predicting the surface roughness of milling U71Mn steel is shown in Figure **8** below. Four inputs and one output are given, and 12 hidden layer nodes are determined.

The error performance curve after network operation is shown in Figure **9** below. As the number of steps increases, the error of the sample is also gradually reduced, it shows that the predicted value of the roughness of the neural network approximates the actual value of the sample set After 24 steps of the error reaches a minimum and the process of the network model is completed.

Table 2: Training Samples

Test serial No	n(r/min)	fz(mm/z)	ap(mm)	ae(mm)	$\overline{Ra}$
1	4000	0.04	1	3	0.321
2	4000	0.10	1.5	15	0.794
3	4000	0.06	2	12	0.335
4	4000	0.12	2.5	9	0.576
5	4000	0.08	3	6	0.368
…	…	…	…	…	…
23	8000	0.04	2	9	0.496
24	8000	0.10	2.5	6	0.395

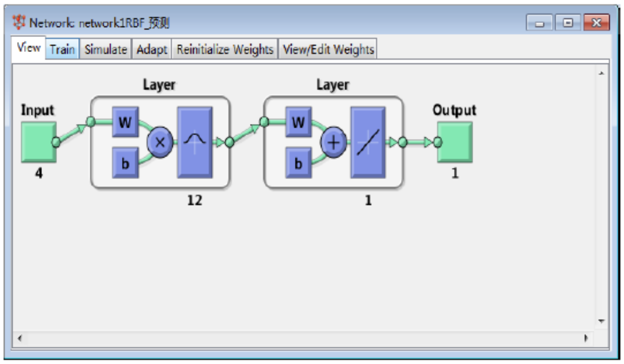

Figure 8: Neural Network set up.

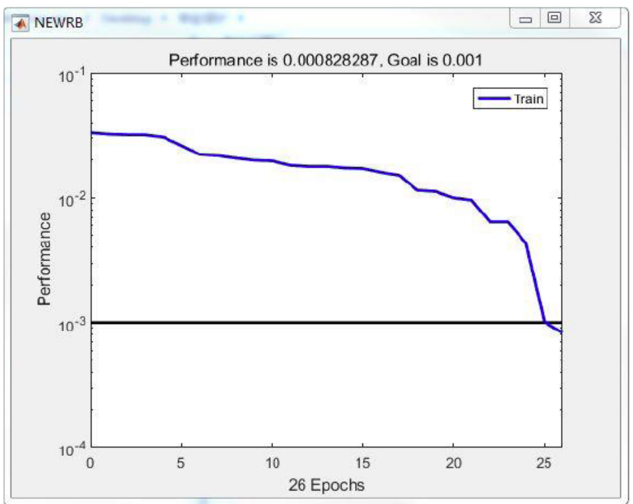

Figure 9: Neural network training steps.

4. PREDICTION RESULTS AND ANALYSIS

In order to fully verify the excellent performance of the neural network prediction, according to the experimental sample data, based on the multiple linear regression method, the empirical formula for predicting the surface roughness is:

$$Ra = 0.7714n^{0.0196} f_z^{0.3026} a_p^{0.0969} a_e^{0.0036} \quad (10)$$

Then, according to the order of orthogonal experiments, the actual roughness value, multiple linear regression value and RBF neural network predicted value of milling U71Mn steel obtained from 25 samples as abscissa coordinates were compared. The experimental value and fitting value of Ra were plotted as shown in Figure **10** below.

It can be seen from the figure that only two of the 25 test samples have a multivariate linear prediction error slightly smaller than the RBF neural network prediction error, and the neural network has a prediction error of only 0.18%, and the RBF neural network model has a higher correlation between the predicted value and the experimental value. The error control is very good, far less than the regression prediction model. The relative error of the 25 groups of experimental samples is less than 5%, which indicates that the established RBF neural network model predicts the excellent surface roughness of the milling U71Mn steel, which is better than the empirical prediction model. Accurate prediction model of the parameter optimization system and the correlation coefficient is 0.995, the intelligent algorithm shows better performance.

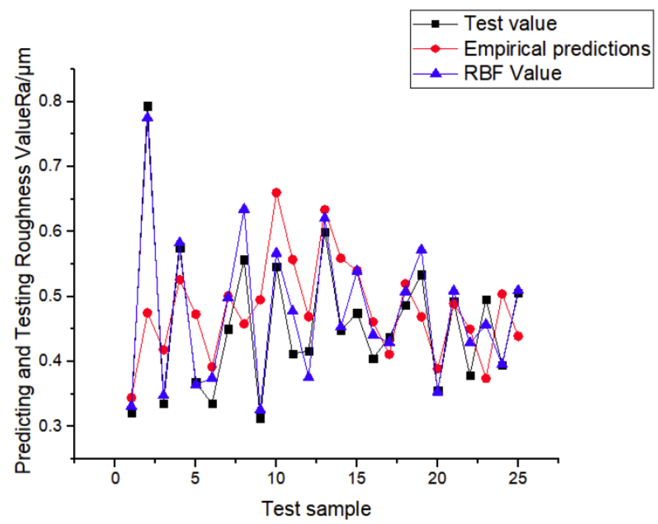

Figure 10: Comparison of two prediction models with actual Ra values.

5. CONCLUSION

In this paper, the radial basis neural network is selected as the theoretical algorithm for predicting the surface roughness of milling U71Mn steel and four milling parameters are selected as the main factors affecting the surface roughness. Based on this, the orthogonal experiment is designed. Through the process of the data sample to complete the neural network modeling, by verifying the prediction of the experimental data, it is proved that the surface roughness prediction model has higher regression accuracy and prediction ability and the surface roughness prediction model based on RBF network and the traditional index. The regression model is compared. From the perspective of prediction accuracy, this prediction model is significantly better than the traditional index model. It has four processing parameters and milling for better description of spindle speed, feed per tooth, axial depth and radial depth. The ability to correlate the surface roughness of high manganese steel to achieve accurate prediction of surface roughness under different milling processing parameters of high manganese steel.

REFERENCE

[1] Chuangbo M. The effect of rail grinding on wheel-rail interaction[J]. Railway Standard Design 2002; (07): 31-32.

[2] Chunlin W, Beibei H, Yiming F, *et al*. Multi-objective optimization of double vane pump based on radial basis function neural network and particle swarm optimization [J]. Journal of Agricultural Engineering 2019; 35(02): 25-32.

[3] Shuaizhe W, Jinmei W, Yongqi W, *et al*. Short-term wind power prediction based on PSO-ICA-BP neural network [J]. Electrical and Electrical 2019; (02): 7-11.

[4] Moody JE, Darken CJ. Fast learning in networks of locally-tuned processing units. Neural Computation 1991; 3(4): 579-581.

[5] Junjun C, Qinghua C. Application of Radial Basis Function Neural Network in Surface Roughness Prediction of High Speed Milling [J]. Combination Machine Tool and Automation Machining Technology 2013; (06): 6-8.

[6] Xianjin T, Zhangqiu, Gang Z, *et al*. Prediction of machined surface roughness of polymer-bonded Explosives Based on radial basis function neural network [J]. Journal of Military Engineering 2014; 35(02): 200-206.

[7] Tatar A, Nasery S, Bahadori A, *et al*. Implementing radial basis function neural network for prediction of surfactant retention in petroleum production and processing industries[J]. Liquid Fuels Technology 2016; 34(11-12): 992-999.
https://doi.org/10.1080/10916466.2016.1177548