Mechanical Performance Prediction of Cold Rolled Ribbed Steel Bars Based on RBF Network with Whole Variable Space

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Abstract. This paper proposes a method of mechanical performance prediction of cold rolled ribbed steel bars based on RBF network with whole variable space. It builds a whole variable space model and studies the performance prediction of cold rolled ribbed steel bars based on the 5-in & 1-out RBF network and the performance prediction of cold rolled ribbed steel bars based on the 5-in & 2-out RBF network. The results show that this method can reliably predict the mechanical performance of cold rolled ribbed steel bars, and the predictive effect of the 5-in & 1-out RBF network model based on whole variable space is superior to the 5-in & 2-out RBF network model.

Introduction

The rolling process of cold rolled ribbed steel bars is a very complex physical process. During the cold rolling process, original materials are subjected to repeated rolling deal, and subjected to an integrated complex constraint. Rolling condition and status are changing constantly. Besides that, the rolling process must be maintained equivalent metal flow each second between racks and comply with the energy conservation law. Therefore, it is very difficult to establish mathematical physics equations between the process parameters of cold rolled ribbed steel bars and product mechanical properties from the perspective of material constraints and geometric deformations directly [1].

This paper studies on mechanical performance prediction of cold rolled ribbed steel based on whole variable space and Radial-Basis Function (RBF) neural network. It provides mechanical performance prediction of cold rolled ribbed steel bars with theoretical basis and scientific method by using the whole variable space features and the high precision approximation performance of RBF network.

The Establishment of Whole Variable Space [2-8]

Taking any process parameter vector as a predictive sample, and denoted by $\boldsymbol{x}^{(c)}$ which has five components, and denoted by $x^{(c)}{}_j$ (j = 1, 2, …, 5). The five components represent five process parameters of cold rolling [3], i.e., the tensile strength of the raw material, the reducing amount of rolling, drawing speed, amount of fluctuation in rolling mill scroll wheel and scroll wheel spacing.

It use $\boldsymbol{x}_i$(i = 1, 2, …, 24)to mark the known variables in sample space, and the components of $\boldsymbol{x}_i$ mark as $\boldsymbol{x}_{ij}$, where the evaluation of 'j' is defined as above.

Using formula (1) to calculate the Euclidean distance between $\boldsymbol{x}^{(c)}$ and $\boldsymbol{x}_i$:

$$d_i = \left\| x^{(c)} - x_i \right\|_2 = \left[\sum_j (x^{(c)}{}_j - x_{ij})^2 \right]^{\frac{1}{2}} \tag{1}$$

According to above formula, it can calculate the distance between predictive samples $\boldsymbol{x}^{(c)}$ and all known samples $\boldsymbol{x}_i$, which marked as d_i. Then, according to d_i, it picks an appropriate number of known samples $\boldsymbol{x}_i$ from sample space to constitute training sample subspace $\boldsymbol{P}^{(c)}$ (samples in which marked as $\boldsymbol{x}^{(c)}{}_i$) which aimed to the predictive samples $\boldsymbol{x}^{(c)}$.

The Product Performance Prediction Based on 5-in & 1-out RBF Neural Network [2-8]

The five inputs of RBF network are same respectively the tensile strength of the raw material σ_0, the reducing amount of rolling $\triangle$, drawing speed v, amount of fluctuation in scroll wheel I and scroll wheel spacing s, which denoted by x_i (i = 1, 2, …, 5) in network. The output of RBF network is the tensile strength σ_b or the elongation δ_b of cold rolled ribbed steel bars, which denoted by y_i (i = 1, 2) in network.

Structure of mechanical performance prediction based on 5-in & 1-out RBF neural network model is shown in Fig. 1. In the Fig. 1, the y_1 represents the tensile strength σ_b of cold rolled ribbed steel bars, and the y_2 represents the elongation δ_b of the product.

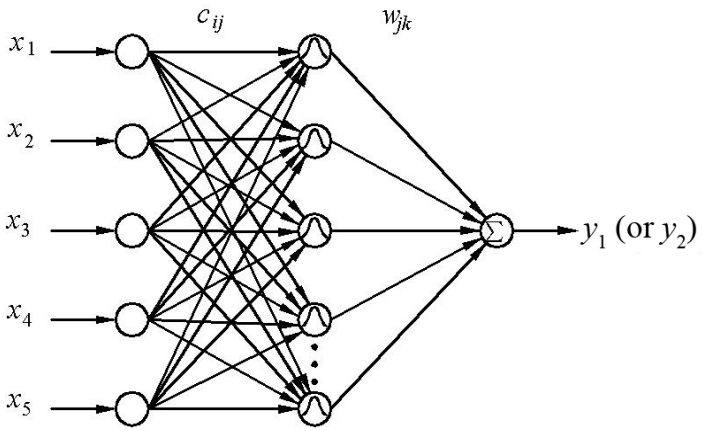

Fig. 1 Structure of 5-in & 1-out RBF network model

Sampling 1, 3, 7, 18, 11, 23, 14 and 24 numbers for the test samples, the rest of the samples in whole variable space are regarded as known samples. It uses the 5-in & 1-out RBF network model to predict the mechanical performance parameters of the product. The experimental results and predictive results of the test samples mechanical performance are listed in Table 1.

Table 1 Predictive results of product mechanical performance based on 5-in & 1-out RBF network with whole variable space

Test samples $\boldsymbol{x}^{(c)}$	Known sample variables $\boldsymbol{x}^{(c)}_i$	Tensile strength σ_b			Elongation δ_b		
		Measured values	Predictive values	Relative errors (%)	Measure values	Predictive values	Relative errors (%)
1	The other samples except the test samples	5.348	5.3189	0.5439	10.8	10.8000	1.5793e-4
3		5.987	5.9870	5.1223e-6	9.0	9.0009	0.0096
7		5.921	5.9311	0.1701	9.3	9.2960	0.0435
18		5.506	5.6069	1.8331	10.3	10.3234	0.2272
11		6.571	6.5861	0.2296	8.1	8.1012	0.0152
23		5.920	5.9200	3.7559e-4	8.4	8.4112	0.1332
14		6.624	6.6240	1.6760e-4	7.2	7.2000	3.8935e-4
24		6.273	6.2730	3.4308e-4	8.1	8.0948	0.0642

As it can be seen by the data in Table 1, all of the relative errors between the predictive values and the measured values are less than 2% through the 16 mechanical performance parameters of product which predicted by the 5-in & 1-out RBF network model with whole variable space, accounting for 100% of the total predictive parameters. The average relative error of the predictive results by this model is 0.204%, and the standard deviation is 0.443. Obviously, it can reach very high predictive accuracy which predicted by the 5-in & 1-out RBF network with whole variable space, when the network neuronal layer width coefficients is reasonable match with the network error.

The data in Table 1 also reflect that the predictive effect of cold rolled steel elongation is superior to the predictive effect of tensile strength which based on 5-in & 1-out RBF network with whole variable space.

The Product Performance Prediction Based on 5-in & 2-out RBF Neural Network [2-8]

Structure of 5-in & 2-out RBF network model is shown in Fig. 2. In the Fig. 2, the y_1 represents the tensile strength σ_b of cold rolled ribbed steel bars, and the y_2 represents the elongation δ_b of the product. Still sampling 1, 3, 7, 18, 11, 23, 14 and 24 numbers for the test samples, the rest of the samples in whole variable space are regarded as known samples. It uses the 5-in & 2-out RBF network model to predict the mechanical performance parameters of the product. The experimental results and predictive results of the test samples mechanical performance parameters are listed in Table 2.

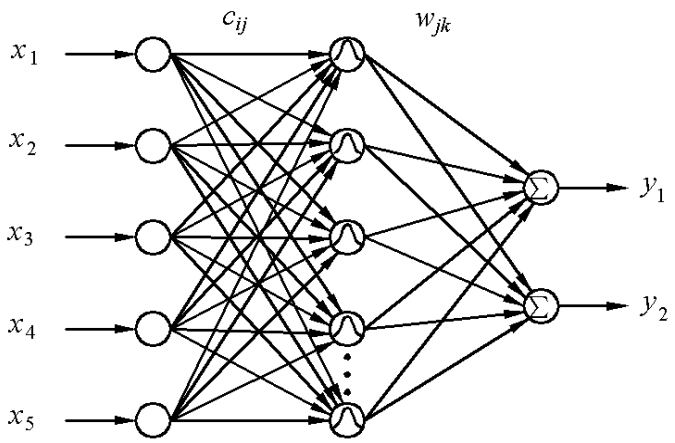

Fig. 2 Structure of 5-in & 2-out RBF network model

Table 2 Predictive results of product mechanical performance based on 5-in & 2-out RBF network with whole variable space

Test samples $x^{(c)}$	Known sample variables $x^{(c)}_i$	Tensile strength σ_b			Elongation δ_b		
		Measured values	Predictive values	Relative errors (%)	Measure values	Predictive values	Relative errors (%)
1	The other samples except the test samples	5.348	5.2721	1.4191	10.8	10.6852	1.0633
3		5.987	5.9853	0.0285	9.0	9.0003	0.0036
7		5.921	5.9003	0.3497	9.3	9.2993	0.0074
18		5.506	5.5029	0.0568	10.3	10.3073	0.0704
11		6.571	6.3508	3.3506	8.1	8.1090	0.1105
23		5.920	5.8712	0.8240	8.4	8.2024	2.3522
14		6.624	6.5152	1.6421	7.2	7.2003	0.0036
24		6.273	6.2776	0.0741	8.1	8.1018	0.0222

As it can be seen by the data in Table 2, there are 14 relative errors between the predictive values and the measured values are less than 2% through the 16 mechanical performance parameters of cold rolled ribbed steel bars which predicted by the 5-in & 2-out RBF neural network with whole variable space, accounting for 87.5% of the total predictive parameters. There are 16 relative errors are less than 5%, accounting for 100% of the total predictive parameters. The average relative error of the predictive results by this neural network model is 0.711%, and the standard deviation is 0.979. It also has very high predictive accuracy to the mechanical performance of cold rolled ribbed steel bars. But, from the whole point of view, its predictive effect is inferior to the effect which predicted by the 5-in & 1-out RBF neural network with whole variable space and the 5-in & 1-out RBF neural network with dividing variable space according to distance between technological variables.

Conclusions

Compared the predictive results of the 5-in & 1-out RBF network based on whole variable space listed in Table 1 with the predictive results of the 5-in & 2-out RBF network listed in Table 2, it is found that the former is 0.204% while the latter is 0.711% from the average relative error of predictive results, and the predictive accuracy of the former is higher than the latter's. From the standard deviation of predictive results, the former is 0.443 while the latter is 0.979, and predictive stability of the former is higher too. So, from the whole point of view, just like the former predictive model, the predictive effect of the 5-in & 1-out RBF network based on whole variable space is more excellent.

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