International Forum on Energy, Environment Science and Materials (IFEESM 2017)

Mechanical Properties Prediction of Cold Rolled Ribbed Bars based on Full Sample Space and BP Neural Network

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Keywords: Whole variable space, BP neural network, Cold rolled ribbed steel bars, Mechanical properties

Abstract. This paper proposes a method of mechanical performance prediction of cold rolled ribbed steel bars based on BP neural network with whole variable space. It builds a whole variable space model and studies the mechanical performance prediction of cold rolled ribbed steel bars based on the 5-in & 1-out BP network and the mechanical performance prediction of cold rolled ribbed steel bars based on the 5-in & 2-out BP 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 BP network model based on whole variable space is superior to the 5-in & 2-out BP network model.

Introduction

During the cold rolling process of ribbed steel bars, 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.

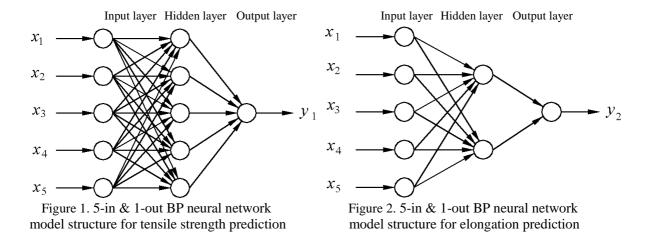
This paper studies on mechanical performance prediction of cold rolled ribbed steel based on whole variable space and BP neural network. It provides mechanical performance prediction of cold rolled ribbed steel bars with theoretical basis and scientific method by using the whole variable space features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

Prediction Modeling of Mechanical Properties of Cold Rolled Ribbed Bars Based on Full Sample Space

When dividing variable space according to whole variable space, the inputted samples of prediction model are five-dimensional vectors in each built subspace. The mechanical performance prediction model of cold rolled ribbed steel bar is established by using 5-in & 1-out and 5-in & 2-out BP neural network. The 5 inputs of BP neural network are the tensile strength of the raw material σ_0 , the reducing amount of rolling Δ , drawing speed v, the 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 BP neural network is the tensile strength σ_b or the elongation δ_b of cold rolled ribbed steel bars, which denoted by y_k (i = 1, 2) in network.

For the mechanical properties prediction model of cold rolled ribbed steel bars based on the 5-in & 1-out, Taking into account the factors of the stability and the network training time and the predictive accuracy of network predicted results, it uses 5 nodes in hidden layer of BP network when predicting the tensile strength of product, and it uses 2 nodes in hidden layer of BP network when predicting the elongation of product after multiple tests. The model structures of them are shown in Figure 1 and Figure 2. In the figures, 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 it.





For the mechanical properties prediction model of cold rolled ribbed steel bars based on the 5-in & 2-out, it uses 2 nodes in hidden layer of BP network, and the structure is shown in Figure 3.

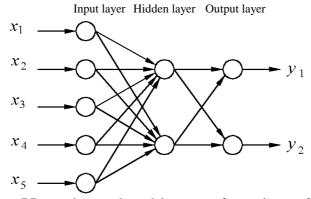


Figure 3. 5-in & 2-out BP neural network model structure for product performance prediction

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

Mechanical Performance Prediction of Product Based on 5-in & 1-out BP Neural Network

After multiple tests, it uses 10 nodes in hidden layer of 5-in & 1-out BP neural network when predicting the tensile strength of product, and it uses 11 nodes in hidden layer of BP network when predicting the elongation of product. Sampling 2, 4, 6, 8, 10, 12, 16 and 20 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 BP neural 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.

As it can be seen by the data in Table 1, there are 5 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 & 1-out BP neural network with whole variable space, accounting for 31.3% of the total predictive parameters. There are 13 relative errors are less than 5%, accounting for 81.3% of the total predictive parameters. There are 16 relative errors are less than 10%, accounting for 100% of the total predictive parameters. The average relative error of the predictive results by this model is 3.35%, and the standard deviation is 2.3.

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



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

| Test samples $x^{(c)}$ | Known sample | Tensile strength σ_b | | | Elongation δ_{b} | | |
|------------------------|---|-----------------------------|-------------------|--------------------|-------------------------|-------------------|--------------------|
| | variables $x^{(c)}_i$ | Measured values | Predictive values | Relative errors(%) | Measure values | Predictive values | Relative errors(%) |
| 2 | The other samples except the test samples | 5.663 | 5.7686 | 1.86 | 9.5 | 9.7138 | 2.25 |
| 4 | | 6.123 | 6.0253 | 1.60 | 8.5 | 8.6456 | 1.71 |
| 6 | | 5.728 | 5.8874 | 2.78 | 10.5 | 10.128 | 3.54 |
| 8 | | 6.121 | 6.3125 | 3.13 | 8.7 | 8.2815 | 4.81 |
| 10 | | 6.352 | 6.6291 | 4.36 | 8.4 | 8.8562 | 5.43 |
| 12 | | 6.713 | 6.9625 | 3.72 | 7.8 | 8.1214 | 4.12 |
| 16 | | 6.785 | 6.4237 | 5.32 | 6.5 | 6.8976 | 6.12 |
| 20 | | 6.460 | 6.5428 | 1.28 | 7.5 | 7.3823 | 1.57 |

Mechanical Performance Prediction of Product Based on 5-in & 2-out BP Neural Network

After multiple tests, it uses 13 nodes in hidden layer of 5-in & 2-out BP neural network when predicting the tensile strength of product. Sampling 2, 4, 6, 8, 10, 12, 16 and 20 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 BP neural 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 2.

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

| Test samples $x^{(c)}$ | Known sample variables $x^{(c)}_i$ | Tensile strength $\sigma_{\rm b}$ | | | Elongation δ_b | | |
|------------------------|---|-----------------------------------|-------------------|--------------------|-----------------------|-------------------|--------------------|
| | | Measured values | Predictive values | Relative errors(%) | Measure values | Predictive values | Relative errors(%) |
| 2 | The other samples except the test samples | 5.663 | 5.7425 | 1.40 | 9.5 | 9.6347 | 1.42 |
| 4 | | 6.123 | 6.0356 | 1.43 | 8.5 | 8.6378 | 1.62 |
| 6 | | 5.728 | 5.8745 | 2.56 | 10.5 | 10.224 | 2.63 |
| 8 | | 6.121 | 6.3057 | 3.02 | 8.7 | 8.3941 | 3.52 |
| 10 | | 6.352 | 6.5983 | 3.88 | 8.4 | 8.7829 | 4.56 |
| 12 | | 6.713 | 6.9458 | 3.47 | 7.8 | 8.0619 | 3.36 |
| 16 | | 6.785 | 6.4387 | 5.10 | 6.5 | 6.8712 | 5.71 |
| 20 | | 6.460 | 6.5341 | 1.15 | 7.5 | 7.4015 | 1.31 |

As it can be seen by the data in Table 2, there are 6 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 BP neural network with whole variable space, accounting for 37.5% of the total predictive parameters. There are 14 relative errors are less than 5%, accounting for 87.5% of the total predictive parameters. There are 16 relative errors are less than 10%, accounting for 100% of the total predictive parameters. The average relative error of the predictive results by this model is 2.88%, and the standard deviation is 1.96.

The data in Table 2 also reflect that the predictive effect of tensile strength is superior to the predictive effect of cold rolled steel elongation which based on 5-in & 1-out BP neural network with whole variable space.

Conclusions

The predictive effect of the tensile strength is superior to the predictive effect of the elongation on the whole according to mechanical performance of cold rolled ribbed steel bars, whether it based



on 5-in & 1-out BP neural network or 5-in & 2-out BP neural network with whole variable space. Besides that, the predictive effect of 5-in & 2-out BP neural network is superior to predictive effect of 5-in & 1-out BP neural network.

Acknowledgement

This research was financially supported by the Six Talent Peak Project in Jiangsu Province (2012-ZBZZ-038) and Xuzhou Science Technology Project (KC16SG243).

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