2009 International Conference on Computational Science and Engineering

Prediction and Key Computer Programming of Mechanical Properties of Hot Rolled Plate Based on BP Neural Network

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Abstract

Based on the theory of artificial neural network,BP algorithm is used for the training of networks,and the relationship between the controlling parameters in hot rolling (temperature, rolling press, chemical composition, cooling rate, etc) and the parameters of mechanical properties is established, key computer programming has been determined. The calculation results are in good agreement with the experimental results.

1. Introduction

In the process of steel rolling, the basic principles of many problems are clear, however, it is difficult to carry out the scientific processing and establish the definite mathematical model. Since most of the quality indexes of the steel such as mechanical property are obtained onsite testing and empirical formula due to the non-linear characteristics of processing parameters, chemical compositions and mechanical property, it has a certain limitation; as a result, it cannot effectively carry out the prediction and testing of the mechanical property of the steel [1, 6-11].

Compared with the traditional empirical modeling tools, the artificial neural network has many advantages as an empirical modeling tool [2, 6-7]. It has unique advantage in solving the problems with indistinct rules and many component variables and can conclude the rules from the existing experimental data; although it cannot define the functional form of this rule, the trained neural network can be used for direct reasoning.

This paper establishes BP neural network model for mechanical property of steel with the onsite production data of the hot rolling plant. After trained, this neural network can effective predict the mechanical property of the rolled steel. After testing, elevation and calculation, the results are very identical with the test results.

2. Mathematical model of neural network

Neutral network is a kind of hierarchy neutral network with three layers or more, shown in Fig. 1, and is a three-layer feed-forward neural network. It comprises of input layer, hidden layer (intermediate layer) and output layer; input layer has i nodes, hidden layer has j nodes and output layer has t nodes. The neurons between upper layer and lower layer are completely connected, that is, each unit in the lower layer is completely connected with the one in the upper layer while each neuron in each layer has no connection. The network studies in form of the instruction by teachers; when a pair of studying modes are supplied to the network, the actuation value of the neuron promulgates from the input layer to the output layer via each intermediate layer and each neuron in input layer acquires the input response of network. Then modify each connection weight value from the output layer via the each intermediate layer one by one as per the direction of the error between the reduced desired output and the actual output, and then return to input layer [3-5].

Algorithm steps:

978-0-7695-3823-5/09 $26.00 © 2009 IEEE
DOI 10.1109/CSE.2009.102

1) Set the initial weight system $w(0)$ as the relatively smaller random nonzero value.

2) Given input/output sample pair, calculate the output of the network.

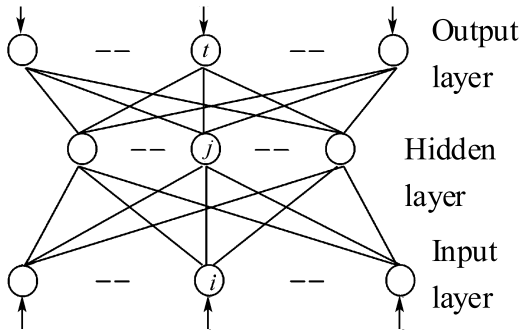


Figure 1. Sketch map of typical BP network

Suppose the input and the output of the sample in Group p are respectively

$$u_p=(u_{1p},u_{2p},\cdots,u_{np})$$

$$d_p=(d_{1p},d_{2p},\cdots,d_{np}) \qquad p=1,2,\cdots,L$$

Output of Node i in inputting the sample in Group p is

$$y_{ip}=f[x_{ip}(t)]=f\left[\sum_j w_{ij}(t)I_{jp}\right] \qquad (1)$$

where, I_{jP}—Input j *of* node i in inputting the sample in Group p,

f is the excitation function, adopting Sigmoid Type, then

$$f(x)=\frac{1}{1+e^{-x}} \qquad (2)$$

The input of node of network output layer can be acquired from input layer to output layer via hidden layer.

3) Calculating the objective function J of the network

Set E_p as the objective function of network in inputting sample in Group p, given norm L_2, then

$$E_p(t)=\frac{1}{2}\left\|d_p-y_p(t)\right\|_3^2$$

$$=\frac{1}{2}\sum_k\left[d_{kp}-y_{kp}(t)\right]^2=\frac{1}{2}\sum_k e_{kp}^2(t) \qquad (3)$$

Where, $y_{kp}(t)$ is the output of the network after adjusting weight valve for t times in inputting the sample and k is the node k of output layer.

The general objective function of network is

$$J(t)=\sum_p E_P(t) \qquad (4)$$

as the assessment of network studying condition. Discrimination if

$$J\leqslant\varepsilon \qquad (5)$$

Where, ε is determined preliminarily and $\varepsilon\geqslant 0$, then the algorithm is over. Otherwise turn to Step (4).

4) Back propagation calculation

Carry out reverse calculation from output layer with the method of "gradient descent" based on J, and adjust the weight value layer by layer.

$$w_{ij}(t+1)=w_{ij}(t)-\eta\frac{\partial J(t)}{\partial w_{ij}(t)} \qquad (6)$$

$$=w_{ij}(t)-\eta\sum_p\frac{\partial E_p(t)}{\partial w_{ij}(t)}=w_{ij}(t)+\Lambda w_{ij}(t)$$

Where, η —step length or named as rate of learning. In this paper, given n is 1000000 and η is 0.015.

3. Experimental program and calculation results

3.1 Experimental program

Analyze the onsite production data of Q215A hot strip of unit 1780 of hot rolling plant and determine that the influence from processing parameters and chemical components is relatively large on mechanical property of products is large based on the elementary steel rolling theory [3, 8-11]. The multilayer feed-forward network BP model for back propagation with error is adopted and the network is divided into three layers: input layer, hidden layer and output layer. Select seven parameters including rolling temperature, rolling speed, rolling pressure, cooling water temperature and content percentage of C, Si, and Mn as the input nodes. Select tensile strength, yield strength and elongation as the output node. Detailed plan [4] is shown in Fig. 2.

In BP neutral network, it is important to select the number of nodes in hidden layer, which will directly affect the quality of result. The following empirical formula: $s=\sqrt{n+q}+a$ can be adopted, where s is the number of nodes in hidden layer, n and p are the number of input and output nodes and a is the constant

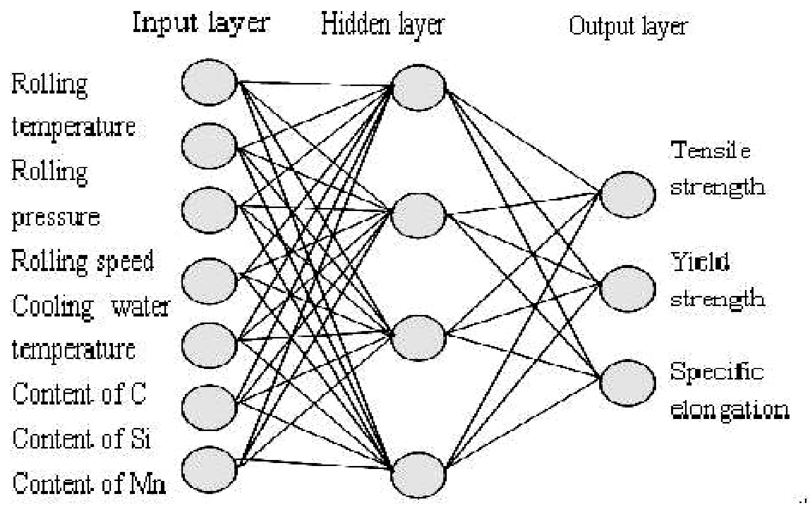


Figure 2. Network design scheme for predication of mechanical property of rolled steel

from 1~10. After validated by the experiment, this network proves that convergence rate is swift when the number of nodes in hidden layer is 12. Select 200 groups of sample data preliminarily and delete the unreasonable samples firstly. In order to improve the training efficiency of neutral network based on the relatively little training samples, adopt orthogonal analysis to screen the onsite production data and finally determine 158 groups of sample data as training samples.

Since the nodal value of neutral network is defined between 0~1, the input value is subject to standardized processing. If a certain node value in input layer is 0, the information input at this node cannot be promulgated to the hidden layer and the output layer. To avoid this situation, the standardized processing for information input adopts the following formulas:

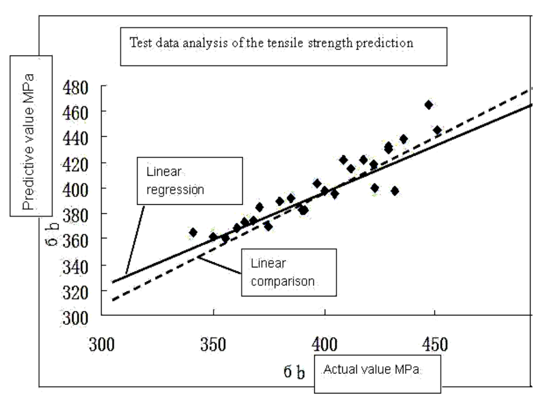
$$S_i = 0.8 \frac{V_i - V_{i\min}}{V_{i\max} - V_{i\min}} + 0.1 \quad (7)$$

Where, V_i is the variable i; $V_{i\min}$ and $V_{i\max}$ are minimal value and minimal value of the variable respectively. Establish three-layer BP network with VC++ programming language according to the above-mentioned design key-points. In training, the initial studying efficiency is set as 0.3, factor of momentum is 0.8 and determine the step width of studying increase. η =0.015 as the training parameter, the total error is 0.25 after training for 150 000 times.

3.2 Prediction results

Select 26 groups of data not trained to complete the testing and assessment of BP network. Adopt simple linear regression method. Analyze the experimental value and predicated value, shown in Figs. 3, 4 and 5.

Maximum error of yield strength σb is 7.03% and the correlation coefficient of actual value and predicted value is 0.83237. Maximum error of yield strength δs is 6.06% and correlation coefficient of actual value and predicted value is 0.877596. Maximum error of elongation δ5 is 7.63% and correlation coefficient of actual value and predicted value is 0.932369. It is shown by the experimental data that the network predication accuracy of this BP is relatively high.



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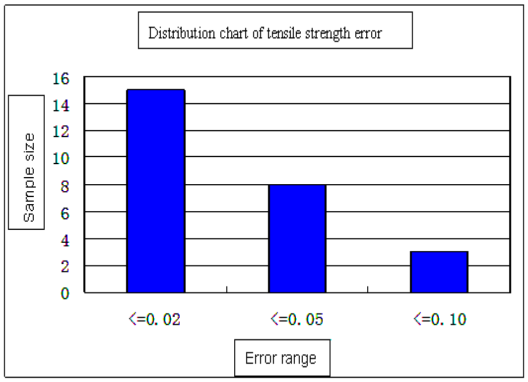
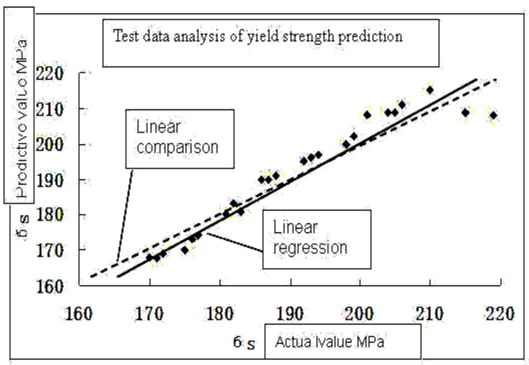


(b)

Figure 3. Comparison between actual and predicated value of tensile strength and distribution chart of predication error



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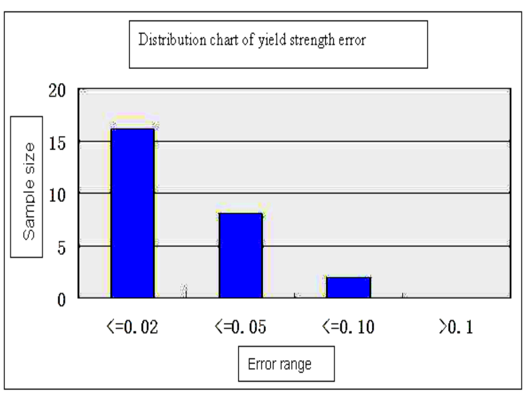
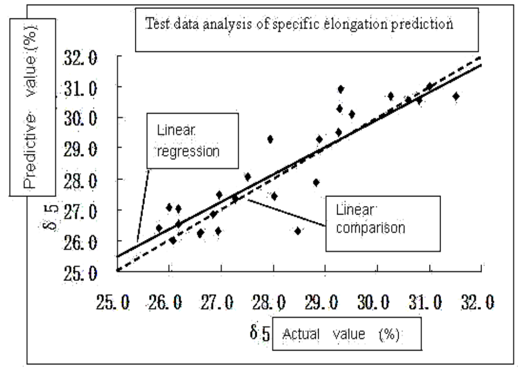
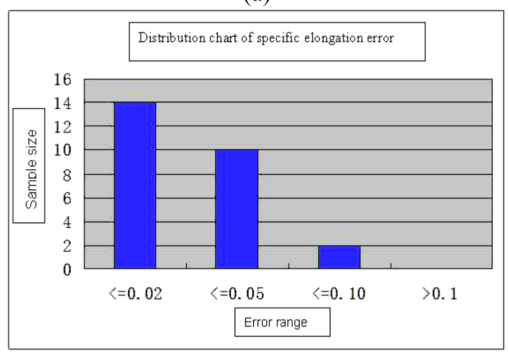


(b)

Figure 4. Comparison between actual and predicated value of yield strength and distribution chart of predication error



(a)



(b)

Figure 5. Comparison between actual and predicated value of specific elongation and distribution chart of predication error

3.3 Key program

```
    // BP neutral network begin trained
    for(l=0;l< lStep;l++)
    {
    //take mean square error
    is 0
    ex=0;
    //take the samples scanning one by one
    for(k=0;k<num;k++)
    {
        // passing to input layer by the proper
    vector of samples extracted
        for(i=1;i<=n_in;i++)
            input_unites[i] = data_in[k][i-1];
        //take setof ideal output passing to BP
    neutral network of ideal output unit.
        for(i=1;i<=n_out;i++)
            target[i]=data_out[k][i-1];
        // passing forward activating
        // passing the data from input layer to
```

```
hidden layer
        bpnn_layerforward(input_unites,hidden_
unites, input_weights, n_in,n_hidden);
        // passing output of hidden layer to
output layer

        bpnn_adjust_weights(hidden_deltas,
n_hidden, input_unites, n_in,input_weights,
input_prev_weights, eta, momentum);
        // error statistical
        for(i=1;i<=n_out;i++)

 ex+=(output_unites[i]-data_out[k][i-1])*(outp
ut_unites[i]-data_out[k][i-1]);
 }
 //calculating mean square error
  ex=ex/double(num*n_out);
  // if mean square error is enough small，to
break the loop，trained end
  if(ex<min_ex)break;
}
```

4. Conclusions

Apply the theory and algorithm of BP neutral network in the predication and research of mechanical property of steel rolling and establish the mapping model of technical parameters, chemical components and mechanical property. After assessment and testing, this BP network is capable of excellently predicating the mechanical property of steel rolling products and supplying the valuable reference for engineering application.

Acknowledgements

It is funded by Hubei Digital Textile Equipment Key Laboratory Funds. （No：DTL200903）

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