The Analysis of Influencing Factors of Steel Bar's Property by Neural Network

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Abstract—This paper presents an analysis of influencing factors of rolled steel bar's property by a novel neural network (NN) computational method. Through the learning process of NN, the nonlinear and complicated relationships among bar's mechanical properties, billet chemical compositions and rolling parameters could be clearly obtained in accordance with the influence rates (IR) calculated for all possible influencing inputs. Such an analysis method could be further developed into an artificial intelligent mechanism which can not only help the technician without full experience to precisely set the relevant control parameters in the steel bar's manufacturing process, but also help the company to produce the high quality steel bar.

Index Terms—influencing factors, steel bar, neural network, mechanical property.

I. INTRODUCTION

It is known that the quality of steel bar is very important to the security of building and human's life. Many countries have set the standard regulations for the qualities of steel bars [1-2]. According to the regulation, any disqualified steel bar must be melted and reproduced. Undoubtedly, such a policy will certainly affect the cost of the steel company. Thus, how to control the quality of steel bar to meet the custom's request and the regulations becomes an important issue for the steel company. In general, yield point (YP), tensile strength (TS) and elongation are three mechanical properties used to evaluate the qualities of steel bar. The chemical quantities of C (Carbon), Si (Silicon), Mn (Manganese), P (Phosphorus), S (Sulfur) are also regulated for the qualified bars [1-2].

In fact, in the manufacturing process, the mechanical properties of steel bar are highly correlated with the compositions of billet and the relevant control parameters of rolling process, such as nominal diameter, rolling speed, hydraulic pump and water's segment. The relationships among bar's mechanical properties, billet chemical compositions and rolling parameters are very complicated and hard defined. In the real manufacturing process, all rolling parameters are usually determined by the technician with full experiences based on the information of Carbon equivalent (C.E.), Carbon (C), Cupper (Cu) and Manganese (Mn). Consequently, such a parameter's setting method according to human's experience easily makes the qualities of steel bar be failure.

In recent years, NN technique has been widely employed into many applications due to its powerful learning and mapping capabilities. Through a simple training process, NN is able to develop the complicated and nonlinear relationship between input and output pairs. Such a well-trained neural model then can be used to perform a specific work. Due to the capability of NN, the predictions and analyses of mechanical property of steel bar by using NN technique have been proposed in articles [3-9].

Table 1 lists the example of steel bar's data collected for study. The information of data includes the mechanical properties of steel bars, billet chemical compositions and relevant rolling parameters. D19, D25, D32 and D39 are size number of steel bar. This research is expected to find the real important influence factors for the steel bar's properties. In our study, a novel NN technique for simplifying the modelling between steel bar's mechanical properties and their relevant influence factors is developed. Through NN's efficient training, the influence rate (IR) of each input variable to the desired output can be obtained. According to the influence rate of each input variable, the real and most important of influence factors to the output then can be determined easily. The proposed method can not only bypass the complicated steps of the statistical analysis, but also clearly verify the correlations of all possible input variables to the system output.

Table 1. The example of data studied.

Type	D19	D25	D32	D39
С	0.2188	0.2088	0.1949	0.2065
Si	0.1647	0.1153	0.0978	0.1004
Mn	0.6625	0.7016	0.7149	0.6576
P	0.0179	0.0339	0.0283	0.0203
S	0.0292	0.0375	0.0345	0.0345
Cu	0.2571	0.3557	0.2545	0.2162
Sn	0.0171	0.0203	0.0219	0.0356
Ni	0.0776	0.0908	0.0744	0.0772
Cr	0.1247	0.1191	0.1232	0.1143
Mo	0.0202	0.0237	0.0143	0.0152
V	0.0038	0.0044	0.0045	0.0051
Nb	0.005	0.0049	0.0051	0.005
C.E.	0.3512	0.3502	0.3357	0.336
Height	1.54	1.95	2.47	2.37
Pitch	12.4	16.2	20.3	24.7
Gap	5.3	5.2	6.1	6.7
Rolling Speed (m/s)	13	10	6.1	4
Pump	3	3	3	4
Segment	3	4	4	4
TS	66.5	68.1	67.4	65.1
YP	54.8	57.4	55.4	53

II. NEURAL NETWORK METHOD

In our research, the supervised multi-layered feed-forward NN is used and the error back-propagation (BP) learning algorithm is taken for NN's training [10-12].

In order to find the importance of each input to the output while NN is well-trained, a novel computational method for the influence rate (IR) of each input variable to the system output is developed and its algorithm is simply described as follows [13-14]. In our studies, the sigmoid function is taken to be the activation function for all NN's nodes. It is an increasing function which has the output value within the range [0, 1]. Here, we use a simple three-layered neural model with size 2-3-1 to describe the whole IR computational method. Its structure is shown in Fig. 1.

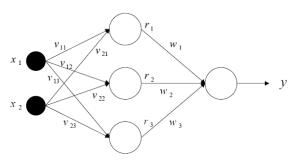


Fig. 1. The structure of 2-3-1 NN model.

In Fig. 1, due to the sigmoid function has the increasing character, the following relationships among the inputs (x_1, x_2) , the outputs of hidden nodes (r_1, r_2, r_3) and the output node (Y) can be derived as

$$r_j \propto \sum v_{ij} x_i + \theta_j \tag{1}$$

$$Y \propto \sum w_j r_j + \theta_0 \tag{2}$$

$$Y \propto \sum w_j (\sum w_{ij} x_i + \theta_j) + \theta_0 \tag{3}$$

 v_{ij} is the strength of connection between hidden node j and input node i; w_j is the strength of connection between hidden node j and output node. θ_0 and θ_j are bias terms. The influence rate (IR) and the percentage influence rate (PIR) of input x_i to the output Y are defined by

$$IR_{i} = \sum_{k=1}^{NT} |\sum_{i} v_{j}(k) w_{ij}(k) x_{i}(k)|$$
(4)

$$PIR_{i} = \sum_{i=1}^{IR_{i}} IR_{i}$$
(5)

where, NT is the total number of input x_i and m is the category's number of input.

III. RESEARCH EXPERIMENTS

In our studies, 836 sets of data, including the billet compositions, control parameters of rolling process and mechanical properties of steel bar, are analyzed and simulated. 558 sets of data are used for NN's training and 278 sets of data are used for test. Through the training of NN, the nonlinear and complicated relationships among bar's mechanical properties, billet chemical compositions and rolling parameters could be accurately developed. According to the influence rates (IR) calculated for all inputs, the real and important influencing factors of bar's mechanical properties could be clearly defined. The NN model with size m-19-1 is used for all simulations.

A. 1st Experiment

In this study, two 19-19-1 neural models for catching the relationships between two mechanical properties and their possible relevant inputs are simulated, respectively. Two mechanical properties are yield point (YP) and tensile strength (TS). For each neural model, there are nineteen inputs, including C, Si, Mn, P, S, Cu, Sn, Ni, Cr, Mo, V, Nb, C.E., height, pitch, gap, rolling speed, pump and segment. The mean absolute error (MAE) and the mean absolute percentage error (MAPE) are used for NN's performance measures. Table 2 lists the error statistics of TS and YP performed by NN.

After NN's training, the values of IR and PIR of each input are calculated by the method we developed. Table 3 lists the IR and PIR information of TS versus inputs and YP versus inputs.

Table 2. The error statistics of TS and YP by using 19 inputs.

Property	TS		YP	
NN	Training	Test	Training	Test
MAE	1.1839	1.1903	1.3248	1.2692
MAPE	1.77%	1.78%	2.41%	2.30%

Table 3. IR and PIR information of TS and YP versus inputs.

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	TS	TS		
	IR	PIR	IR	PIR
С	1.872	6.76	1.064	5.15
Si	1.264	4.69	1.542	7.47
Mn	4.238	15.74	3.453	16.72
P	0.205	0.76	0.124	0.60
S	0.209	0.78	0.115	0.56
Cu	1.747	6.49	1.443	6.99
Sn	0.152	0.56	0.100	0.48
Ni	0.523	1.94	0.327	1.58
Cr	1.414	5.25	1.327	6.43
Mo	0.094	0.35	0.075	0.37
V	0.015	0.06	0.017	0.08
Nb	0.028	0.10	0.020	0.10
C.E.	4.536	16.85	1.508	7.30
Height	1.963	7.29	1.696	8.21
Pitch	1.103	4.10	0.818	3.96
Gap	1.841	6.84	2.238	10.84
Rolling speed	0.427	1.59	0.327	1.58
Pump	3.777	14.30	2.241	10.86
Segment	1.570	5.83	2.213	10.72

In Table 3, it is clearly found that the PIR values of P, S, Sn, Mo, V, Nb are all less than 1%. We boldly assume that these six inputs are not the important influencing factors of TS and YP.

B 2nd Experiment

In this experiment, we remove P, S, Sn, Mo, V, Nb from the inputs of NN and redo the modeling of TS and YP by using the rest of sixteen inputs, C, Si, Mn, Cu, Ni, Cr, C.E., height, pitch, gap, rolling speed, pump and segment. Table 4 lists the error statistics of TS and YP by using thirteen inputs. From the results shown in Table 2 and Table 4, we found that the values of MAE and MAPE of TS and YP are almost the same. It evidences that the assumption we did is correct. The chemical compositions, P, S, Sn, Mo, V, Nb can be deleted and have no influence to the mechanical properties TS and YP.

Table 4. The error statistics of TS and YP by using 13 inputs.

Property	TS		YP YP	
NN	Training	Test	Training	Test
MAE	1.1845	1.1934	1.3260	1.2705
MAPE	1.77%	1.79%	2.41%	2.30%

C 3rd Experiment

Generally, in the compositions of billet, C, Cu, Mn and C.E. are four main reference factors taken by the technician who is full of experiences to set the values of control parameters in the manufacturing process. Thus, in this experiment, only ten influencing factors, including C, Mn, Cu, C.E., height, pitch, gap, rolling speed, pump and segment, are used for NN inputs. Table 5 lists the error statistics of TS and YP by using ten inputs.

Table 5. The error statistics of TS and YP by using 10 inputs.

Property	TS		YP	
NN	Training	Test	Training	Test
MAE	1.2236	1.2146	1.3617	1.2966
MAPE	1.83%	1.82%	2.47%	2.35%

From the results shown in Table 2, Table 4 and Table 5, it can be found that the values of MAE and MAPE of TS and YP are increased, but not much. This evidences the reason why C, Cu, Mn and C.E. are four main reference factors in the steel bar's manufacturing process.

IV. CONCLUSION

This research aims to develop a technical method to analyze the real and important influencing factors for the mechanical properties of steel rolling bar. From the simulation results, it can be clearly found that the influence rate (IR) calculated by NN computational method developed indeed is able to obtain the real influencing factors of steel bar's properties. In this study, the billet compositions, P, S, Sn, Mo, V, Nb can be treated as having no correlation with the

bar's properties. However, due to the composition regulation of quantities of C, Si, Mn, P, S for the qualified bar, the quantities of P and S still have to meet the standard. Thus, according to the study results shown, we conclude that this method could be further developed into a practical artificial intelligent mechanism which can help the technician to precisely set the relevant control parameters in the steel bar's manufacturing process. It has a great commercial potential in the real application.

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