Journal of University of Science and Technology Beijing
Vol.6(1999), No.4, p.289

Materials

Modeling and Optimizing of Deformed Steel Bars Hot Rolling

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(Received 1999-05-04)

Abstract: Based on experimental data, a nonlinear model about tensile strength and technical parameters such as Mn and Si content, finishing rolling speed and finishing rolling temperature for deformed steel bars in the process of hot rolling was established by using artificial neural networks. The model can be optimized with a genetic algorithm. The optimum rolling parameters were obtained.

Key words: artificial neural networks; modeling; genetic algorithm; optimizing

Deformed steel bars are widely used in construction engineering. The tensile strength is the main parameter that determines whether deformed steel bars are good or not. In the process of hot rolling, there are many factors influencing the tensile strength of deformed steel bars, such as Mn and Si content, finishing rolling speed and finishing rolling temperature. Finishing rolling speed and finishing rolling temperature can affect the tensile strength by changing the microstructure of the steel base [1]. The suitable addition of Mn and Si can strengthen the steel base, but the excessive addition of Mn and Si can decrease the tensile strength because of the educts at the grain boundary [2]. Further more, the effects of these factors are reciprocal. Thus, in the process of deformed steel bars hot rolling, there exists a complicated nonlinear relationship between the tensile strength and the technical parameters, which is not to be determined by conventional regression methods.

Based on experimental data this paper made a nonlinear model about the tensile strength and the technical parameters by using artificial neural networks, and optimized the optimum technology with a genetic algorithm successfully.

1 Modeling with Artificial Neural Networks

Artificial neural networks (ANN) has been widely used to realize modeling, estimation, prediction, diagnosis and adaptive control in complex nonlinear system [2–8]. The back-propagation (BP) network is a multilayer feedforward and full-connected neural networks. It has strong associative memory and generalization capabilities, and can have approximately any nonlinear continuous function with an arbitrary precision. A 3-layered feed-forward neural networks with 4 neurons in the input layer, 2 neurons in the hidden layer and 1 neuron in the output layer was used in this paper (shown in **figure** 1). Layer I was the input layer which used linear elements including the Mn content Z_1, the Si content Z_2, the finishing rolling speed Z_3 and the finishing rolling temperature Z_4. Layer II was the hidden layer which used nonlinear elements. The input of element j was N_j representing the sum of the outputs of layer I after timing weight respectively, and the output of element j was Y_j representing the result of the nonlinear function of N_j named as $f(x)$. Layer III was the output layer which used only one nonlinear element whose input N_j was the sum of the outputs of layer II (Y_j) after timing weight respectively, and the output, also the output of ANN, was the tensile strength of deformed steel bars (H) which was the result of the nonlinear function of N_j named as $f(x)$. V_{ji} was the connection weight between the input layer and the hidden layer, and W_j the weight between the hidden layer and the output layer.

The learning algorithm of ANN referred to reference [9].

24 samples were randomly selected to train the ANN

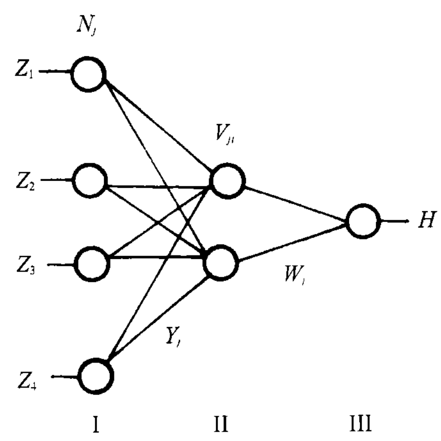

Figure 1 Back-propagation structure of artificial neural networks.

and the remaining 4 samples to verify the generalization capability of the ANN. After 1.116×10^5 iterations, the outputs H of the ANN were close enough to the desired outputs D, not only for the training samples but also for the testing samples. The results were shown in **table 1**. The maximum of relative error was 4.9%. This fact showed that the ANN was good enough.

2 Optimizing with a Genetic Algorithm

After modeling the relationship between H and (Z_1, Z_2, Z_3, Z_4) by using ANN, a nonlinear function was got containing 4 variables, $H=(Z_1, Z_2, Z_3, Z_4)$. The aim of this paper was to find a proper group (Z_1, Z_2, Z_3, Z_4) to maximize H, that was a nonlinear optimization problem. The conventional gradient methods generally encountered one difficulty, that is, they often result in a local maximum.

A genetic algorithm could overcome the difficulty that gradient methods encountered since it was a kind of optimization algorithm based on the law of evolution of living things, *i.e.*, survival of the fittest, natural selection, inheritance and variation. Considering a nonlinear optimization problem in n dimensions:

$$C=f(x_1,x_2,\cdots,x_n) \tag{1}$$

m points within n dimensions were randomly selected to construct the population, and C was used to evaluate every individual, superior and inferior. The genetic algorithm was summarized as follows:

(1) Compute C_i ($i=1,2,\cdots,m$) for each point. Half of the population would survive and the surviving probability was proportional to the corresponding value of C_i for the ith individual.

(2) Crossbreed. Copy the $m/2$ surviving individuals firstly and pair them randomly, then exchange part elements of each pair randomly to generate new individuals.

Table 1 ANN training and predicating points.

Sample	w_{Mn} / %	w_{Si} / %	Finishing rolling speed /m·s^{-1}	Finishing rolling temperature / ℃	Tensile strength / MPa		Relative error / %
					Desired D	Output H	
1	1.32	0.55	15.8	1 025	600	588	2.0
2	1.28	0.51	15.8	1 025	630	622	1.3
3	1.37	0.49	15.7	1 025	655	647	1.2
4	1.26	0.48	15.7	1 025	630	623	1.1
5	1.39	0.58	15.7	1 025	605	579	4.3
6	1.31	0.50	15.6	1 045	665	659	0.9
7	1.31	0.52	15.6	1 045	650	618	4.9
8	1.28	0.51	15.6	1 045	630	626	0.6
9	1.38	0.53	13.4	1 080	645	652	1.1
10	1.32	0.51	13.4	1 080	640	645	0.8
11	1.25	0.46	13.4	1 080	650	638	1.8
12	1.38	0.49	13.4	1 080	710	711	0.1
13	1.32	0.51	13.4	1 080	690	677	1.9
14	1.20	0.49	12.7	1 120	650	636	2.2
15	1.26	0.48	12.7	1 120	630	618	1.9
16	1.28	0.52	12.7	1 120	665	666	0.2
17	1.37	0.53	12.7	1 120	620	608	1.9
18	1.26	0.47	12.5	1 136	615	619	0.6
19	1.35	0.51	12.5	1 136	600	606	1.0
20	1.29	0.47	12.5	1 136	625	624	0.2
21	1.30	0.53	12.5	1 136	620	623	0.5
22	1.40	0.61	12.5	1 136	610	618	1.3
23	1.32	0.44	12.5	1 136	605	587	1.3
24	1.35	0.54	12.5	1 136	635	639	0.6
25*	1.32	0.48	12.5	1 136	605	612	1.2
26*	1.32	0.58	15.6	1 045	685	678	1.0
27*	1.20	0.56	13.4	1 080	655	656	0.2
28*	1.31	0.46	12.7	1 120	680	688	1.2

Note: * represents the testing samples.

(3) Mutation. Select several individuals randomly in the population, and mutate some elements in the selected individuals (add a small random number).

(4) A new generation was generated. Return to (1) and start to breed next generation. In this way the whole population would move to the area which corresponded to high C values. At last, some individual was close enough to the maximum of f.

For an example, the C content of the deformed steel bars is 0.2%, the number of hot rolling pass is 16, the shape of the deformed steel bars changes from 120 mm $\times$120 mm to ϕ20 mm, $m = 28$ and $n = 4$. After the genetic algorithm worked over 8.5×10^3 iterations, the optimization point was (1.34%, 0.45%, 13.5, 1 076), *i.e.*, the optimum parameters were 1.34% for the Mn content, 0.45% for the Si content, 13.5 m/s for the finishing rolling speed, 1 076℃ for the finishing rolling temperature, and the corresponding H, namely, the maximum tensile strength of deformed steel bars was 714 MPa. This optimum technology was verified through further experiments. The experimental data are shown in **table 2**.

Table 2 Optimum experimental data.

Sample	w_{Mn} / %	w_{Si} / %	Finishing rolling speed /m·s^{-1}	Finishing rolling temperature / ℃	Tensile strength / MPa
1	1.34	0.45	13.5	1 076	714.2
2	1.34	0.45	13.5	1 076	714.1
3	1.34	0.45	13.5	1 076	714.0
4	1.34	0.45	13.5	1 076	714.0
5	1.34	0.45	13.5	1 076	713.9
6	1.34	0.45	13.5	1 076	713.9

3 Conclusions

In the process of deformed steel bars hot rolling, the nonlinear model about the tensile strength and the technical parameters (such as Mn content, Si content, finishing rolling speed and finishing rolling temperature) can be constructed by using artificial neural networks very well. Artificial neural networks as an advanced technique offer a new way for solving the problem on modeling of deformed steel bars hot rolling. Moreover, a genetic algorithm based on the law of evolution of living things can optimize the model successfully.

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