Z. M. CAI, H. C. JI, W. C. PEI, X. M. HUANG, W. D. LI, Y. M. LI
ISSN 0543-5846
METABK 57(4) 191-195 (2018)
UDC – UDK 669.15.26.24.74.786:620.17-536.45:62.001.57:513.4.6/620.16/539.374=111

CONSTITUTIVE MODEL OF 3Cr23Ni8Mn3N HEAT-RESISTANT STEEL BASED ON BACK PROPAGATION (BP) NEURAL NETWORK(NN)

Received – Primljeno: 2019-01-17
Accepted – Prihvaćeno: 2019-03-25
Original Scientific Paper – Izvorni znanstveni rad

The 3Cr23Ni8Mn3N heat-resistant steel was subjected to isothermal constant strain rate compression experiments using a Gleeble - 1 500D thermal simulator. The thermal deformation behavior in the range of deformation temperature 1 000 - 1 180 °C and strain rate 0,01 - 10 s^{-1} was studied. Based on experimental data, the stress-strain curves of 3Cr23Ni8Mn3N were established. And the constitutive relation of BP neural network (3 × 10 × 10 × 1) was constructed. The flow stress was predicted and compared by the ANN constitutive model. The correlation coefficient (R) is 0,999, and the average relative error (AARE) is 0,697 %. The results show that the ANN constitutive model has high accuracy for predicting the thermal deformation behavior of 3Cr23Ni8Mn3N. The model can provide a good reference value for thermal processing.

Key words: 3Cr23Ni8Mn3N; artificial neural network; constitutive model; heat - resistant; stress - strain curve

INTRODUCTION

3Cr23Ni8Mn3N (23-8N) is an austenitic heat resistant steel. In recent years, due to the characteristics of diesel engines (high power, low energy consumption, high temperature), it is widely used in medium and large size machinery. At present, the commonly used steels for high-power diesel exhaust valves are 53Cr21Mn9Ni4N and 4Cr14Ni14W2Mo, which are mainly used in the exhaust and intake valves below 700 °C. However, with the continuous development of technology, the requirements for diesel engine valves have increased. The existing material steel grades are no longer sufficient for their demand (economical, corrosion resistance, thermal strength). Therefore, some countries use austenitic heat-resistant steel to manufacture gas valves. 33Cr23Ni8Mn3N is a Cr-Ni-N type austenitic heat-resistant steel. The differences are that the carbon and nitrogen contents are increased, the nickel is reduced by 3,5 % and chromium is increased by 2 %. These changes not only maintain a stable austenite structure but also material properties (high temperature resistance, gas resistance, cost performance). In addition, the advantages of this material have been proved to improve the function of the valve, save costs and improve the material sensitivity in the valve manufacturing process.

Z. M. Cai, H. C. Ji, W. C. Pei, X. M. Huang, W. D. Li, Y. M. Li. College of Mechanical Engineering, North China University of Science and Technology, Hebei, Tangshan, China; H. C. Ji (E-mail: jihongchao@ncst.edu.cn), College of Mechanical Engineering, North China University of Science and Technology, Hebei, Tangshan, China; National Center for Materials Service Safety, University of Science and Technology Beijing, China; School of Mechanical Engineering, University of Science and Technology Beijing, Beijing, China;

At present, many scholars use the Arrhenius equation regression model to establish the constitutive model of materials. For example, Lin et al. [1] established the constitutive equation of 45CrMo material, Sun et al. [2] established the constitutive equation of AZ31 magnesium alloy, Li et al. [3] established peak constitutive equation of 21-4N heat-resistant steel. However, the Arrhenius equation belongs to the regression model, the internal dynamic response of the material during thermal deformation is also a very complicated process. There are certain deficiencies in relational prediction. Artificial Neural Network (ANN) has been widely used in engineering because it can effectively find complex nonlinear relationships [4,5]. Error Back Propagation Network (BP Network) is one of the most widely used and successful neural networks. There are already some scholars who have established neural network models for material constitutive relations. For example, Wang et al. [6] used the PSO-BP neural network to establish the constitutive model of Ti-10.2Mo-4.9Zr-5.5Sn alloy. Sun et al. [7] established the high temperature constitutive relation of Ti-22Al-25Nb by BP neural network method, and compared with the results calculated by traditional regression fitting method. The comparison shows that the prediction accuracy of the BP neural network constitutive model is significantly better than the traditional model. Senthilkumar et al. [8] investigated a comparison between ANN and different constitutive models which shows that the ANN model has a higher accuracy in estimating the flow stress during thermal deformation of AA5 083 / 2 % TiC nanocomposite. Chen et al. [9] compared the prediction accuracy of the BP neural network model and the Zerilli – Armstrong model for the flow stress of pure molybdenum, and proved that BP neural network model is more accurate than Zerilli – Armstrong model. Li et al. [10] established constitutive equations and neural network models respectively, which proved that neural networks are more valuable. Sani et al. [11] compared constitutive equation and ANN model in amagnesium alloy.

The above shows that the constitutive model of materials using BP neural network provides a good reference value for the thermal deformation behavior of materials. In addition, the constitutive relationship model of the thermoplastic deformation behavior of materials established by BP neural network can greatly reduce the limitations brought by traditional regression methods. The BP neural network constitutive model of metal materials has been recognized by many scholars at home and abroad.

In this paper, based on the thermal simulation isothermal compression test data of 3Cr23Ni8Mn3N, the flow stress constitutive model of 3Cr23Ni8Mn3N is established by BP neural network. The stress of the material is predicted, which indicates that the established BP model has high precision for stress prediction of 3Cr23Ni8Mn3N. It is of great significance to better determine the thermal processing parameters of the 3Cr23Ni8Mn3N.

EXPERIMENTAL MATERIALS AND PROCESSES

The experimental material is 3Cr23Ni8Mn3N heat-resistant steel, and its chemical composition (in wt.%) is 0,38 C - 0,95 Si - 2,30 Mn - 7,02 Ni - 0,38 N - 24 Cr - (bal.) Fe. The sample size is Φ 8 mm × 15 mm. The alloy is subjected to isothermal constant strain rate compression deformation test on a Gleeble - 1 500D thermal stress simulation test machine. The test data of stress, strain, displacement, temperature and time are automatically collected by a computer system. The deformation temperature T is 1 000, 1 060, 1 120, and 1 180 °C, respectively, and the strain rate range of 0,01, 0,1, 1, 10 s^{-1}. The degree of deformation is 60 %. According to the experimental results, the stress - strain curves are established as shown in Figure 1.

NEURAL NETWORK CONSTITUTIVE MODEL

The BP model usually consists of three parts: the input layer, the hidden layer and the output layer. Each layer contains several neurons. The neurons in different layers are connected to each other, and the neurons in the same layer are unconnected to each other. Its structure is shown in Figure 2. Input data is passed from the input layer to the hidden layer and the output layer by the transfer function. When the error between the output data and the actual data is too large, the neural network propagates the error signal back, and continuously modify the weight of each layer of the neural network to adjust the output result according to the situation. Train-

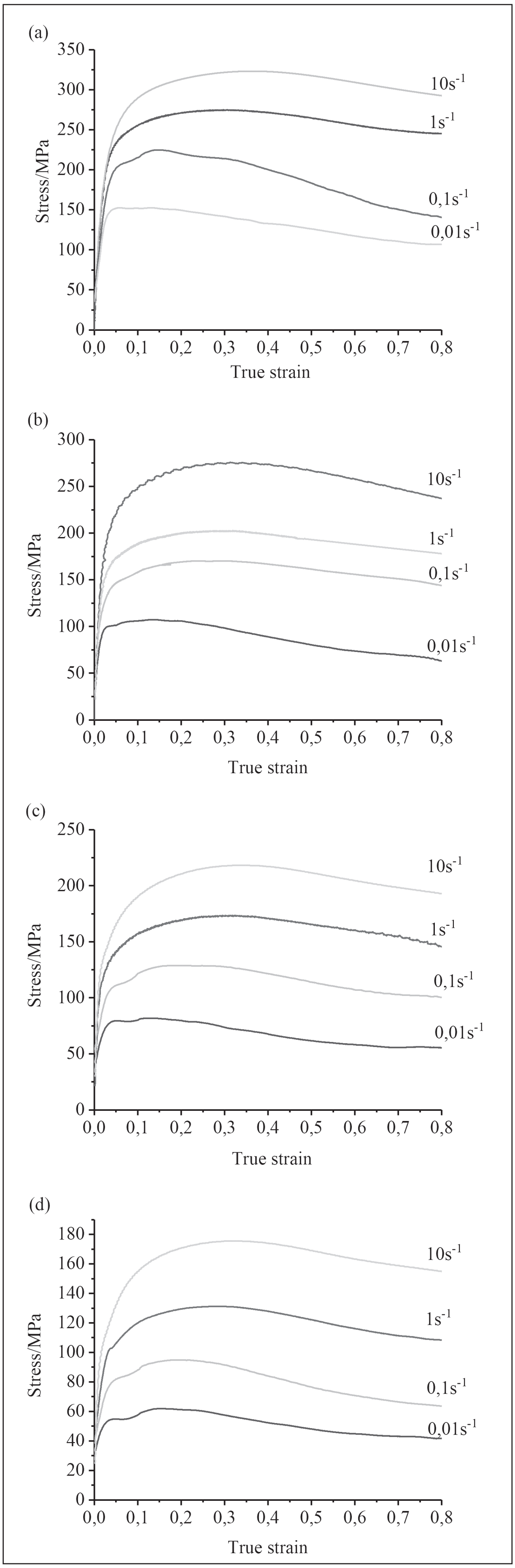

Figure 1 True stress – strain curves of 3Cr23Ni8Mn3N obtained by hot simulation compression tests. (a) T = 1 000 °C; (b) T = 1 060 °C; (c) T = 1 120 °C; (d) T = 1 180 °C.

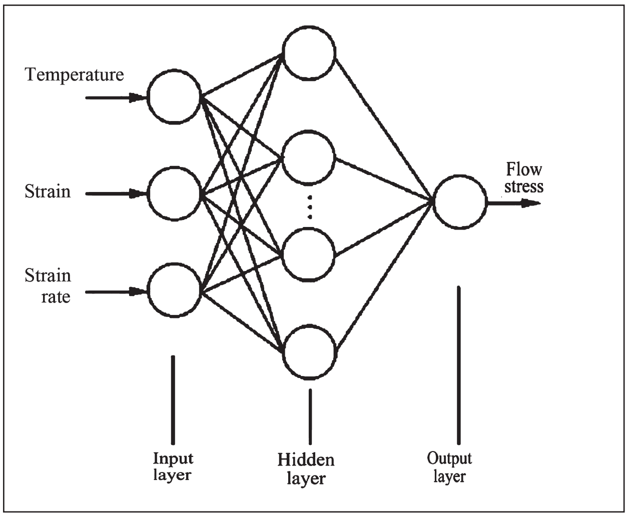

Figure 2 Schematic map of BP neural network

ing is completed when the output error reaches the desired set point.

The specific operation flow of the BP neural network model is as follows.

(1) Initialization, each connection weight and threshold of the network model is assigned a random value in the interval [- 1,1].

(2) The input sample *x*, the target output *y* and the target precision θ are determined.

(3) Calculate the actual output. Calculate the output of each unit of the hidden layer and the output layer in turn:

$$y_j = \int(\sum_{j=0}^{n} w_{ij} x_i) \quad (1)$$

$$\int(x) = \frac{1}{1+e^{-x}} \quad (2)$$

In the equation, y_j is the output of node *j*, $\int(x)$ is the Sigmoid function; w_{ij} is the connection weight between the input layer and the hidden layer; x_i is the input of node *i*.

(4) Calculate the error between the target value and the actual value *E*.

$$E = \frac{1}{2}\sum_{j=1}^{n}(Y_j - y_j)^2 \quad (3)$$

In the equation, Y_j is the ideal output.

(5) Weight correction

$$w_{ij}(n_0)+(1) = w_{ij}\, n_0 - \eta H \quad (4)$$

In the equation, n_0 is the number of trainings; η is the variable that controls the speed of the weight modification; *H* is the weight increment $H = \frac{\partial E}{\partial W_{ij}} = -\sum_{p=1}^{p} \delta_{pj} x_i$, and δ_{pj} is the error term of the *j*-node in the *p*-mode.

(6) Calculate hidden layer unit error:

$$w_{ij}(n_0)+(1) = w_{ij}\, n_0 - \eta H \quad (4')$$

(7) If the error $E < \theta$, the training is completed, otherwise go to step (2) until the accuracy requirement is met.

ESTABLISHMENT OF BP CONSTITUTIVE MODEL

In order to accurately describe the dynamic response of 3Cr23Ni8Mn3N steel stress to thermal parameters, a BP neural network model is used to construct the constitutive equation, which can be expressed as:

$$\sigma = \sigma(\varepsilon, \varepsilon', \mathrm{T}) \quad (5)$$

These three variables (strain ε, strain rate ε' and deformation temperature T) can be used as input variables, and the output layer is flow stress. The established neural network constitutive relationship model is:

$$\sigma = NN(\varepsilon, \varepsilon', \mathrm{T}) \quad (6)$$

At present, most scholars determine the hidden layers of neural networks and the number of neurons in each hidden layer according to experience. The calculation equation of the number of neurons in the hidden layer is as follows:

$$n = \sqrt{N+M} + m \quad (7)$$

n is the number of neurons in the hidden layer, *N* is the number of input layer neurons, *M* is the number of neurons in the output layer, *m* is an integer between 1 and 8.

Prior to training, data should be pre-processed. In this paper, the data is normalized using the mapminmax function, the value range is [- 1, 1], and its expression is as follows:

$$Y = \frac{2(X - X_{\min})}{X_{\max} - X_{\min}} - 1 \quad (8)$$

In the equation, *X* is the original vector value; X_{min} and X_{max} are the minimum and maximum values of *X*, respectively; *Y* is the vector value normalized by the *X* vector.

After the preparation is completed, using Matlab's toolbox to program according to the BP network implementation process. Choosing different training functions to train to get the best training results. The training results are shown in Table 1. As can be seen from the table, the error of the trainlm training function is significantly better than the other, using the trainlm function. Likewise, by using different learning functions and activation functions, then comparing BP network error analysis. When the trainlm is a training function, the leanngd is learning function, the activation function of the hidden layer is tansig, and the activation function of the output layer is purelin, the training is best. In the same way, through the selection of different hidden layer structures in the Matlab neural network toolbox for repeated training, the training results are shown in Table 1. According to Table 1, 4 layers (3 × 10 × 10 × 1) neural network structure was selected, which has high precision and is suitable for 3Cr23Ni8Mn3N steel. When the training target is 10^{-3}, after 42 iterations, the system quickly converges and the system error reaches the training target. The convergence curve is shown in Figure 3. As can be seen from Figure 3, the neural network tends to converge quickly, and high precision.

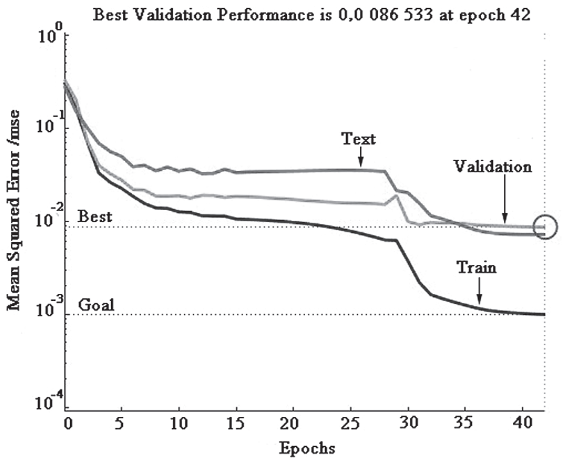

Figure 3 Training convergence curve of BP neural network

Table 1 **Performance of BP neural network model for testing datasets of 3Cr23Ni8Mn3N**

Architecture	Systematic Error		
	Traingdm	Traingdm	Trainlm
3-10-5-1	0,0 858	0,1 450	0,0 041
3-10-6-1	0,0 850	0,1 970	0,0 013
3-10-7-1	0,1 180	0,0 944	0,0 019
3-10-8-1	0,1 000	0,1 710	0,0 013
3-10-9-1	0,0 660	0,1 290	0,0 014
3-10-10-1	0,0 843	0,0 897	0,0 009
3-10-11-1	0,0 954	0,0 813	0,0 011
3-10-12-1	0,0 674	0,0 787	0,0 011
3-10-13-1	0,4 120	0,0 912	0,0 132

MODEL ACCURACY EVALUATION

The advantage of the neural network model is that it can predict the flow stress of the whole process. After the training is completed, the flow stress of 3Cr23Ni8Mn3N heat-resistant steel is predicted by the trained BP neural network model, and the predicted results are compared with the experimental data. The results obtained are shown in Figure 4. The prediction accuracy is very high. To more accurately illustrate the accuracy of the prediction of the equation, the standard statistical parameters were used to calculate the correlation coefficient (R) and the mean absolute relative error AARE (%) according to Equation (9) and Equation (10):

$$R = \frac{\sum_{i=1}^{n}(E_i - \overline{E})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(E_i - \overline{E})^2 (P_i - \overline{P})^2}} \tag{9}$$

$$AARE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_i - P_i}{E_i}\right| \times 100\ \% \tag{10}$$

In the equation, E is the experimental stress, P is the predicted stress, $\overline{E}$, $\overline{P}$ is the average of the experimental and predicted values, and N is the total number of experimental data. Figure 4 shows the comparison between the predicted values of the ANN constitutive model and the experimental values. As can be seen from

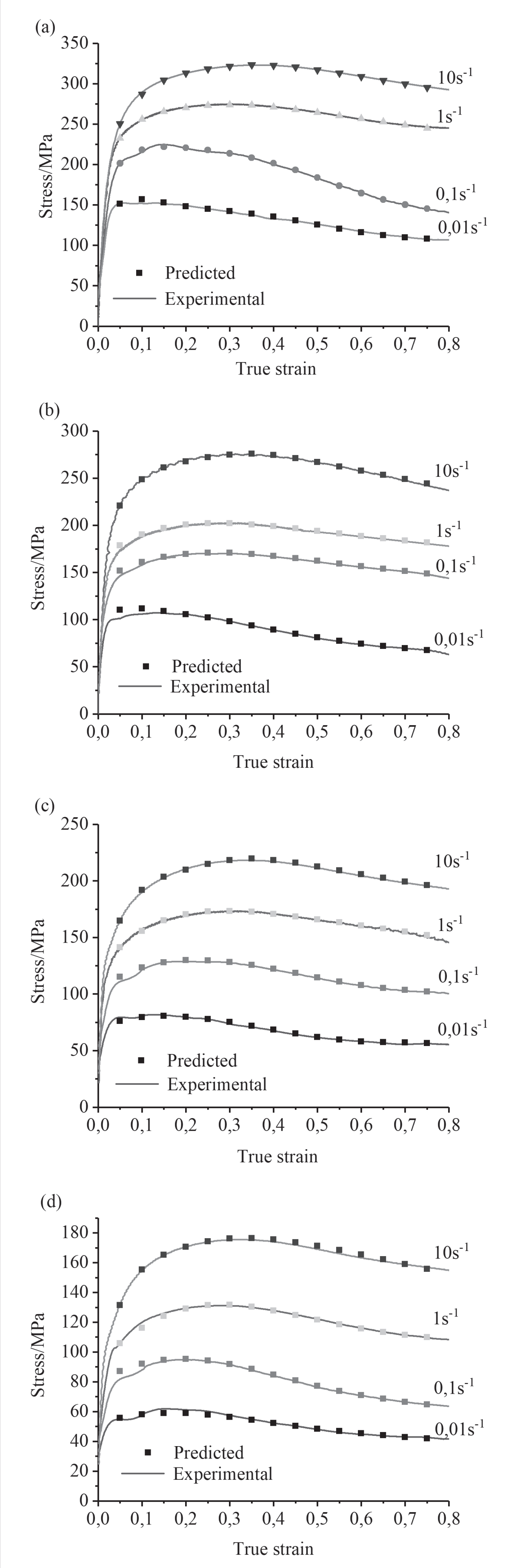

Figure 4 Comparison of predicted values of flow stress and experimental values (a)T = 1 000 °C; (b)T = 1 060 °C; (c)T = 1 120 °C; (d)T = 1 180 °C

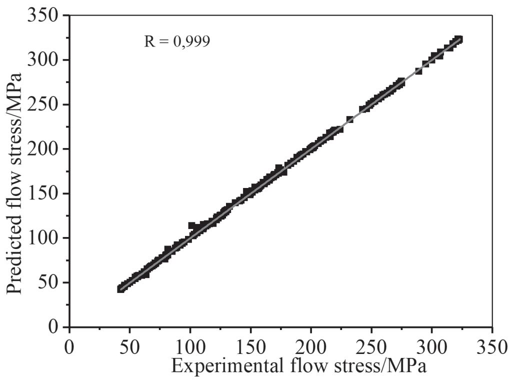

Figure 5 Correlation between experimental stress and predicted stress of 3Cr23Ni8Mn3N.

the figure, the predicted values of each point are almost consistent with the experimental values. This indicates that the BP neural network constitutive model has a high prediction accuracy for the prediction of the 3Cr23Ni8Mn3N flow stress. Figure 5 shows the correlation of the experimental values and the predicted data. It can be seen from the figure that the prediction results are generally highly correlated. Its correlation coefficient is R = 0,999, AARE (%) = 0,697 %. This indicates that the BP neural network model can better predict the flow stress of 3Cr23Ni8Mn3N heat-resistant steel, and provide a theoretical basis for the selection of thermal processing equipment and the formulation of reasonable thermal processing parameters. 10^{-4}

CONCLUSION

(1) The constitutive model of 3Cr23Ni8Mn3N heat-resistant steel established by BP neural network has high precision. After calculation, R = 0,999, AARE (%) = 0,697 %; this indicates that the ANN constitutive model can provide a good reference value for the thermal processing behavior of 3Cr23Ni8Mn3N.

(2) BP neural network model can make up for the limitation of the traditional regression model can't reflect the whole process of deformation.

Acknowledgments

This research was funded by China Postdoctoral Science Foundation (NO. 2018M641186).

COMPLIANCE WITH ETHICAL STANDARD

The authors declare no conflict of interest.

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Note: The responsible translator for English language is Z M Cai-North China University of Science and Technology, China