[Article ID] 1003- 6326(2001)02- 0210- 03

Artificial neural network model of constitutive relations for shock-prestrained copper ①

YANG Yang(杨 扬), ZHU Yuan-zhi(朱远志), LI Zheng-hua(李正华),
ZHANG Xin-min(张新明), YANG Li-bin(杨立斌), CHEN Zhi-yong(陈志永)
(Department of Material Science and Engineering, Central South University,
Changsha 410083, P. R. China)

[Abstract] Data from the deformation on Split-Hopkinson Bar were used for constructing an artificial neural network model. When putting the thermodynamic parameters of the metals into the trained network model, the corresponding yielding stress can be predicted. The results show that the systematic error is small when the objective function is 0.5, the number of the nodes in the hidden layer is 6 and the learning rate is about 0.1, and the accuracy of the rate-error is less than 3%.

[Key words] shock-prestrain; constitutive relations; artificial neural network model

[CLC number] TG146.1^{+}1 **[Document code]** A

1 INTRODUCTION

Shock-prestrained copper is often used in experiments[1~3] for research of the properties of deformation and the formation of adiabatic shear bonds of materials at high strain rate owing to its high ductility. The shock-prestrain process is used to enhance the calorific capacity of unit plastic deformation, accordingly, to increase the flow stress and the sensitivity to strain-rate.

Copper had been previously shock-prestrained at a pressure of 50 GPa, which can increase the yield stress. A few material scientists have studied the constitutive relations of the shock-prestrained oxygen-free high conductivity (OFHC) copper[2,3]. However, the constitutive relations of this material, especially under the condition of high strain-rate ($\dot{\varepsilon}$), are very complex, such as complex dislocation interactions with the formation of sub-grains, inhomogeneities and other peculiarities ensued.

Several models[4~6] have been proposed for these constitutive relations. However, these models were based on dislocations overcoming obstacles by thermal activation. In fact, the deformation mechanism of these materials at high strain-rate is very complex. The relations among the parameters as flow-stress (σ), strain-rate ($\dot{\varepsilon}$), strain(ε) and experiment temperature (T) are nonlinear. Therefore, we may use artificial neural network, which is very useful for expressing nonlinear relations, to establish the constitutive relations of OFHC copper. These artificial neural network models can provide relatively accurate parameters prediction and these predictions can be used in the later researches.

2 ARTIFICIAL NEURAL NETWORK MODEL

After a shock-prestrain on copper (OFHC) at a pressure of 50 GPa[2], samples were gotten to be tested on Hopkinson Bar testing apparatus[7]. The data obtained under the condition of different temperature, different strain and different strain-rate were used for establishing the artificial neural network model.

2.1 Back propagation network model

Multi-layer feedforword neural network is also called back propagation neural network. In this paper, we use the standard feedforword neural network, which is formed by three layers (input, output, hidden) of neurons, as shown in Fig. 1. In this model, the input layer includes three nodes —— $\dot{\varepsilon}$, ε, T, and the output layer includes just one node (σ), while the number of the nodes in the hidden layer depends on the training process. The characteristics of the artificial neural network are: no feedback con-

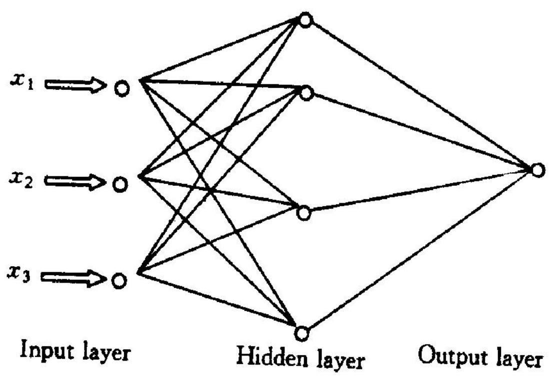

Fig. 1 Model of three-layer feedforward neural network

① [Received date] 2000- 04- 27; [Accepted date] 2000- 08- 01

junction between different layers; no conjunction between neurons within a layer; there are connections just between adjacent neurons. An input signal will be propagated to the hidden nodes, then the signals from the hidden nodes to the output nodes. At last the results will be gotten. We fetch Sigmoid function as the incentive function of the neurons in the hidden layer and linear function as the incentive function of the neuron in the output layer. The output value of the j th neuron from the p th training sample is[8]

$$O_{pj} = f(\mathrm{Net}_j) = \frac{1}{1 + \exp[-(\sum w_{ij} x_j + \theta_j)]} \quad (1)$$

where Net_j is the output of the j th neuron in the hidden layer, θ_j is the threshold of the unit in the hidden layer, w_{ij} is the conjunction weight among the output layer and the hidden layer. By adjusting the conjunction weight between different layers and the threshold between different neurons, modeling of the nonlinear object can be achieved. As to every output data column, if the initial weight of the network has been set arbitrarily, the error (E_p) between the output value of the network and expectation value exists. Here, the objective function for training is as[9]

$$E = \sum_p E_p = \frac{1}{2}\sum_{p=1}^{M}\sum_{j=1}^{N}(O_{pj} - y_{pj}) = E(w_{ij}, w_{jk}, \theta_j, \theta_k) \quad (2)$$

where y_{pj} is the expectation output of the j th output unit in the p th learning sample, O_{pj} is the true output of corresponding network, M is the number of the training samples, N is the number of output nodes.

The maximum gradient descent algorithm is used to make the weight vary in the direction of antigradient of the error function, the weight modification after k times of iteration is as

$$\Delta w_{ij} = -\eta \frac{\partial E(k-1)}{\partial \omega_{ij}^{N}(k-1)} + \alpha \Delta \omega_{ij}(k-1) \quad (3)$$

where $\Delta\omega_{ij}(k) = \omega_{ij}(k) - \omega_{ij}(k-1)$; $\eta \in (0, 1)$ is the learning rate, k is the number of iterations and $\alpha \in (0, 1)$ is the coefficient of the inertia term. Inertia term is used to bring down the error caused by gradient descent as much as possible. When the objective function satisfies the given convergence criterion, the network becomes stable and the training is completed.

2.2 Data preprocessing

If the data have big difference to each other, the effect on radial functions of the smaller ones will be annihilated, which will increase the difficulties to adjust the conjunction weight between the input layer and the hidden layer. Finally the accuracy and the rate of convergence will be influenced. To overcome these shortcomings, the initial data can be normalized as

$$A_i = 0.1 + 0.8 \times (\frac{A - A_{\min}}{A_{\max} - A_{\min}}) \quad (4)$$

where A is the input parameter of network.

3 RESULTS AND DISCUSSION

Here the program of MATLAB ver. 5.2 is used according to the process of the BP network. The initial weight is gotten at random between − 0.5 to 0.5 and the network comes into convergence after 20 000 times of iteration. Fig. 2 shows the comparison of the predicted values from the trained network model with the experimental value of the yielding stress under the condition of different thermodynamics state. The calculation by the model shows that the choices of the parameters of the network model have important effects on the systematic error.

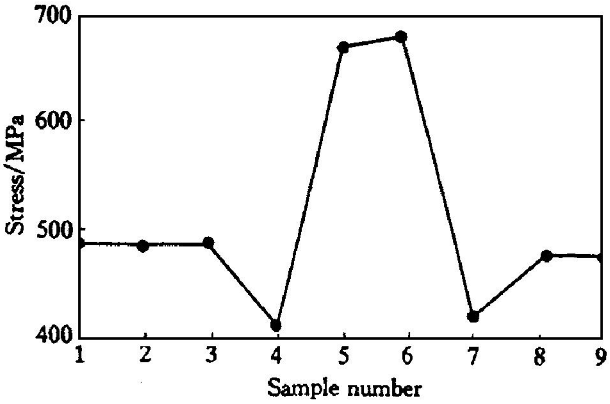

Fig. 2 Predicted curve by network model

The training of the network shows that the systematic error is small when the objective function is 0.5, the number of the nodes in the hidden layer is 6 and the learning rate is 0.1. Table 1 shows the comparison of the model-predicted value with the experimental data of the yielding stress of the shock-prestrained copper. It is obvious that the prediction is accurate enough with the error-rate less than 3%. Fig. 3 shows the comparison of the model-predicted stress-strain relations with the experimental curve. The yielding stress curve is relatively flat for the material having deformed in the form of adiabatic shear, especially at high strain rate. From the above analysis, we can know that our network model is accurate.

4 CONCLUSIONS

In most cases, the experimental data are not so comprehensive due to the limitation of fund, apparatus and so on. If these limited data are put into the artificial neural network model which can learn from the experimental data and generalize the regularity, then the constitutive relations knowledge base of the corresponding metals are formed. Only if we put the

Table 1 Comparison of predicted yielding stress (σ) with experimental data

Sample No.	T/K	ε	$\dot{\varepsilon}$/ s^{-1}	σ_e/MPa	σ_p/MPa	($\sigma_e - \sigma_p$) / MPa	$\frac{\sigma_e - \sigma_p}{\sigma_e}$/ %
1	298	0. 3	2 000	481	488. 99	- 7. 99	1. 66
2	298	0. 4	2 000	487	487. 70	- 0. 7	0. 14
3	298	0. 5	2 000	490. 5	486. 41	4. 09	0. 8
4	573	0. 1	3 500	410	413. 24	- 3. 24	0. 79
5	77	0. 3	3 500	667	658. 37	8. 63	1. 29
6	77	0. 4	3 500	678	677. 21	0. 79	0. 12
7	573	0. 5	3 500	417. 6	413. 24	4. 36	1. 04
8	298	0. 2	0. 1	480. 5	476. 47	4. 03	0. 84
9	298	0. 23	0. 1	482. 3	476. 06	6. 24	1. 29
10	298	0. 06	8 000	512	521. 88	- 9. 88	1. 93
11	298	0. 11	8 000	523	523. 63	- 0. 63	0. 12
12	298	0. 14	8 000	528	525. 25	2. 75	0. 52

σ_e —Experiment data; σ_p —Prediction data

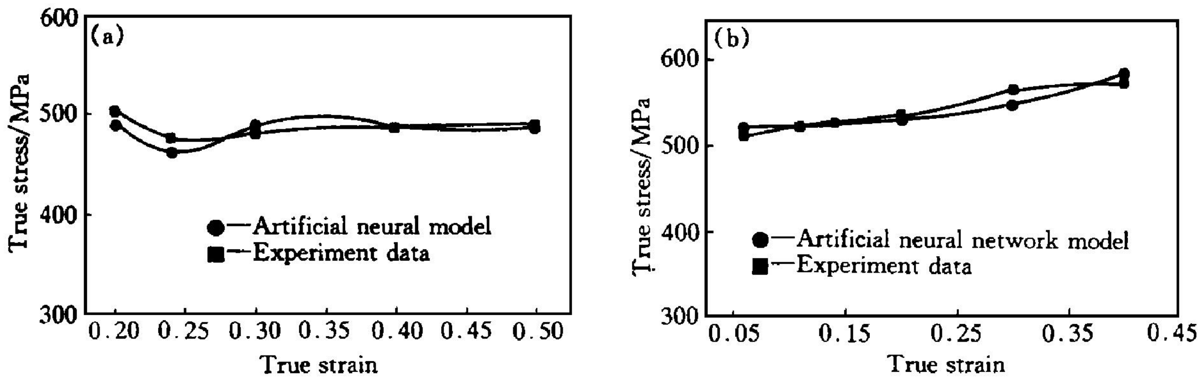

Fig. 3 Comparison of model fitting with experimental data of stress-strain relations
(a) —$\dot{\varepsilon}$= 2 000 s^{-1}, T= 298 K; (b) —$\dot{\varepsilon}$= 8 000 s^{-1}, T= 298 K

corresponding thermodynamic state parameters of the metals into the trained network model, the corresponding yielding stress can be predicted.

[REFERENCES]

[1] CHEN Ming. Neural Network Model, Multi-layer Feed-forward Neural Network [M] . Dalian: Dalian University of Technology Press, 1995. 85.

[2] Andrade U and Meyer M A. Dynamic recrystallization in high-strain high-strain-rate plastic deformation of copper [J] . Acta Metal Mater, 1994, 42(9) : 3183- 3195.

[3] Hines J A and Vecchio K S. Recrystallization kinetics within adiabatic shear bands [J] . Acta Mater, 1997, 45 (2) : 635- 649.

[4] Zerrili F J and Armstrong R W. Dislocation-mechanism-based constitutive relations for material dynamics calculation [J] . J Appl Phys, 1987, 61(5) : 1816.

[5] Follansbee P S and Kocks U S. A constitutive description of the deformation of copper based on the use of the mechanical threshold stress as an internal state variable [J] . Acta Metal, 1988, 36(11) : 81.

[6] WANG Li-li, YU Tong-xi and LI Yong-chi. Shock Kinetics Evolution [M] . Sci-Tech Univ of China Press, 1991. 382.

[7] QI Le-hua, HOU Jun-jie, YANG Fang, et al. An neural network model for direct extrusion in metal solidification [J] . The Chinese Journal of Nonferrous Metals, 1999, 9 (3) : 586.

[8] ZHANG Chuan-xin, PENG Ying-hong and RUAN Xue-yu. An artificial neural network model for Ti-17 alloys [J] . The Chinese Journal of Nonferrous Metals, 1999, 9 (3) : 590.

[9] CHA Tian-Ruo, XIE Shi-ming, DU Bing, et al. An artificial network model for the terminus temperature and carbon content in steel metallurgy [J] . The Chinese Journal of Nonferrous Metals, (in Chinese) , 1999, 9(4) : 868.

(Edited by LONG Huai-zhong)