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Prediction of flow stress of Ti-15-3 alloy with artificial neural network ①

LI Ping(李 萍)[1], SHAN De-bin(单德彬)[1], XUE Ke-min(薛克敏)[1],
LÜ Yan(吕 炎)[1], XU Yi(许 沂)[2]
(1. School of Materials Science and Engineering, Harbin Institute of Technology,
Harbin 150001, P. R. China;
2. Institute of Metal Research, The Chinese Academy of Sciences, Shenyang 110015, P. R. China)

[Abstract] Hot compression experiments were conducted on Ti-15-3 alloy specimens using Gleeble-1500 Thermal Simulator. These tests were focused to obtain the flow stress data under various conditions of strain, strain rate and temperature. On the basis of these data, the predicting model for the nonlinear relation between flow stress and deformation strain, strain rate and temperature for Ti-15-3 alloy was developed with a back-propagation artificial neural network method. Results show that the neural network can reproduce the flow stress in the sampled data and predict the nonsampled data well. Thus the neural network method has been verified to be used to tackle hot deformation problems of Ti-15-3 alloy.

[Key words] artificial neural network; Ti-15-3 alloy; flow stress

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1 INTRODUCTION

Ti-15-3 alloy is a new metastable β-type titanium characterized by improved forge ability and cold formability. It has been used extensively in aerospace industry because of its high specific strength (strength-to-mass rate) which is maintained at elevated temperature. In order to optimize the hot-forging processing conditions for Ti-15-3 alloy it is necessary to understand its deformation behavior at high-temperature conditions[1].

Recently, the fast development of the computing technique leads to a wide application of the finite element approach to the simulation of metal forming process. Numerical simulations with the finite element method can be truly reliable only if it is possible to implement in them an eigen-constitution law describing the material correctly. The eigen-constitution relationship of a material is a foundation in metal-forming theory and technology. In hot deformation, the eigen-constitution model is a highly nonlinear and complex mapping. It is quite difficult to establish the eigen-constitution model using theoretical methods[2].

Recent studies on the application of neural networks have indicated that the neural networks have been quite promising in offering solutions to problems where traditional models have failed or are too complicated to be created. Using a neural network, it is not necessary to postulate a mathematical model at first or identify its parameters. The eigen-constitution relationship of a material can be learned by a neural network through adequate training from experimental data. It can make decisions based on incomplete and disorderly information, but can also generalize rules from those cases on which it was trained and apply these rules to new stimuli. It has been proven mathematically that a three-layer network can map any function to any required accuracy[3, 4].

In this paper, a three-layer feed-forward network with a back-propagation learning rule is employed for acquiring the eigen-constitution relationship of Ti-15-3 alloy. Temperature, effective strain and effective strain rate are used as the input vectors of the network, the output of the neural network is the flow stress. The learning rate is 0.05 and the momentum parameter is 0.15.

2 TESTING METHODS

The compression specimens of Ti-15-3 were of cylindrical geometry, 8 mm in diameter and 12 mm in height, and were compressed on Gleeble-1500 Thermal Simulator. The tests were carried out at constant strain rates of 0.01, 0.1 and 1 s^{-1} to the reductions of 40% and 60% in height at temperatures of 750, 800, 850 and 900 ℃, respectively.

3 ARTIFICIAL NEURAL NETWORK

An artificial neural network simulates biological nervous systems and is referred to as parallel distributed processing system. The network consists of a number of simple processing units known as neurons which communicate in parallel through weighted connections. It is an intelligent information-treatment system with characteristics of adaptive learning and

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treating complex and nonlinear relationships[5~7]. Applying neural networks to the metal forming field is a fairly recent development.

3.1 Feed-forward neural networks

Layers of neural networks are organized into a feed-forward system, in which each neuron within a layer is connected to every neuron in the subsequent layer, but there are no connections between neurons within the same layer. Feed-forward neural networks consist of an input layer, an output layer and hidden layers (see Fig. 1).

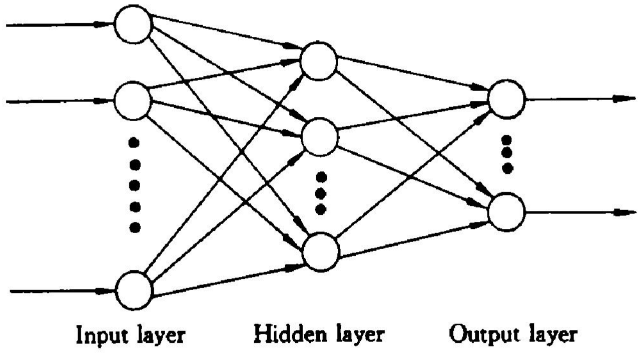

Fig. 1 Structure of feed-forward neural network

The output of each neuron is a nonlinear function of the sum of its inputs. The output function has a sigmoid shape. The explicit function is

$$y_i = f(x_i) = \frac{1}{1+\exp(-x_i)} \tag{1}$$

where y_i is the output of the ith neuron, and x_i is the total inputs of the ith neuron:

$$x_i = \sum_j w_{ij} x_j - \theta_i \tag{2}$$

where w_{ij} is the weight from the jth to the ith neuron, θ_i is the threshold of the ith neuron and x_j is one of the inputs of the ith neuron.

3.2 Configuration and learning algorithm of BP neural networks

Neural networks need to be trained in a learning process before they are applied. Back-propagation algorithm is an extremely effective learning tool that can be applied to a wide variety of problems. First the network is trained by using a predetermined number of input variables. Using the weights of connections between the neurons, the network calculates these results. The results are compared to the desired outputs and the error determines a correction factor for all weights and thresholds which are updated from the output layer to the input layer[8, 9].

Computing the weights and thresholds on the output layer at first, and then propagating the error backwards through the network layer by layer to update, the weights and thresholds are

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_j y_i + \alpha[w_{ij}(t) - w_{ij}(t-1)] \tag{3}$$

$$\theta_i(t+1) = \theta_i(t) + \eta \delta_i \tag{4}$$

where t is the number of weight updates, η is a learning rate($0<\eta<1$), α is a momentum parameter ($0<\alpha<1$), and δ_i is the error gradient of the ith neuron, for the output layer:

$$\delta_i = y_i(1-y_i)(d_i - y_i) \tag{5}$$

where d_i is the desired output.

For the hidden layer:

$$\delta_i = y_i(1-y_i)\sum_j \delta_j w_{ij} \tag{6}$$

The learning rate is changeless in BP learning algorithm. From the error surface of BP networks it can be found that in smooth zone small learning rate increases the iterative times and in rough zone big learning rate increases the error. This is an important reason for BP networks to converge slowly. Therefore the method of changing learning rate is adopted as

$$\eta = \begin{cases} \eta\varphi & (\varphi > 1,\ \Delta E < 1) \\ \eta\beta & (\beta < 1,\ \Delta E > 1) \end{cases} \tag{7}$$

where φ and β are constants, ΔE is error function:

$$\Delta E = E_T(t) - E_T(t-1) \tag{8}$$

The average squared error between the values of desired output and actual output is

$$E_T = \frac{1}{2}\sum_{i=1}^{n}(y_i - d_i)^2 \tag{9}$$

where n is the amount of the sampled data.

3.3 Neural networks eigen-constitution relationship

In hot compression process, the eigen-constitution equation of Ti-15-3 alloy can be written as

$$\sigma = \sigma(\bar{\varepsilon}, \dot{\bar{\varepsilon}}, T) \tag{10}$$

where σ is the flow stress, $\bar{\varepsilon}$ is the effective strain, $\dot{\bar{\varepsilon}}$ is the effective strain rate and T is the deformation temperature.

Therefore, deformation temperature, effective strain and effective strain rate are used as the input vector of the neural network, the output of the neural network is the flow stress. The number of sampled data is 185 sets. All the data should be normalized before being applied to the neural network so that they are confined between 0.1 and 0.9. The data are normalized according to

$$d = 0.8\frac{d - d_{min}}{d_{max} - d_{min}} + 0.1 \tag{11}$$

where d_{min} and d_{max} are the minimum and maximum values of the sampled data respectively.

The number of elements in hidden layer is determined through trial and error. The final network configuration consists of 1 hidden layer with 10 elements. After training, the relative errors between the expected values and the values acquired from the neural network are within 0.1%. Fig. 2 shows the flow stresses acquired from the neural network against those expected and used as training cases. It is found that the accuracy of the prediction of the flow stress is very high. After the neural network training was completed it can be used for predicting other sets of processing data. Fig. 3 shows comparison of the predicted values acquired from the neural network with the non-sampled experimental results. The mean relative error is within 0.2%. It can be observed from the figure that the predictions of the data which were not used for training purpose are also much closer to the experimental data.

4 CONCLUSIONS

Predicting the flow stress of Ti-15-3 alloy with

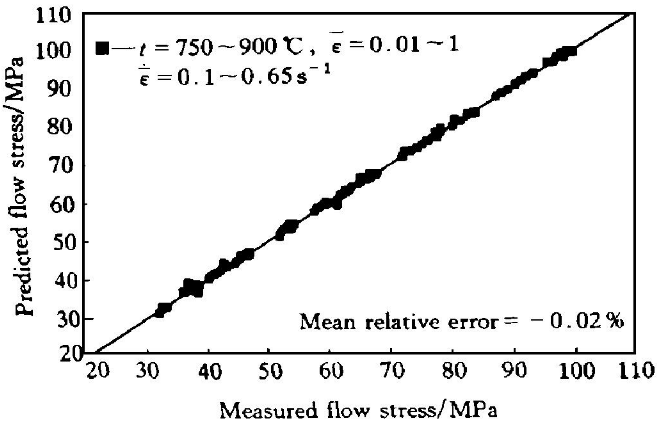

Fig. 2 Comparison of predicted and measured flow stress of sampled data

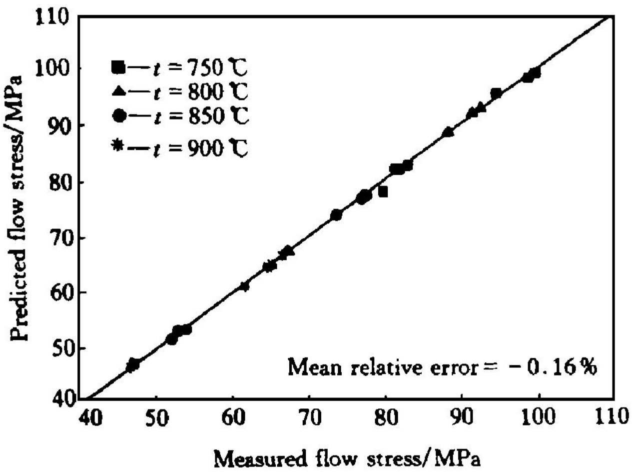

Fig. 3 Comparison of predicted and measured flow stress of non-sampled data

an artificial neural network method not only helps in the reduction of the experimentation required to characterize a flow behavior of a material under the same precision, but also avoids the problems associated with empirical/semi-empirical eigen-constitution models that involve the evaluation of a large number of constants. The trained neural network is able to predict the flow stress very accurately.

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