Z. Y. XUAN, J. L. MIAO

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NEURAL NETWORK-BASED INTRINSIC STRUCTURE RELATIONSHIP OF TC20 TITANIUM ALLOY FOR MEDICAL APPLICATIONS

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Isothermal constant strain rate compression experiments were carried out on TC20 titanium alloy using a Gleeble-1500 thermal simulation tester to investigate its high temperature flow behaviour at deformation temperatures of 750 - 900 °C and strain rates of 0,001 - 1 s^{-1}. The results show that the flow stress basically decreases with increasing deformation temperature and increases with increasing strain rate. The correlation coefficients and mean relative errors were 0,998 and 5,06 % respectively, proving that the BP neural network-based intrinsic structure model is effective in predicting the flow stress of the alloy.

Keywords: TC20 titanium alloy; hot compression; stress-strain curve; constitutive model; BP neural networks

INTRODUCTION

The current increase in medical conditions has led to a growing demand for rehabilitation materials for medical use. Because of its high corrosion resistance and high strength, titanium alloy is 2 - 3 times stronger than steel, but lighter than steel, with a long service life and excellent fatigue resistance, while titanium alloy has good wear resistance, its wear resistance is 7 - 8 times that of steel, which can greatly extend the service life of tools. Therefore, titanium alloys are increasingly becoming the main material used in medical applications.

The intrinsic structure relationship of a material, as the link between the plastic deformation behaviour of the material and the various deformation parameters, is an indispensable part of the information related to the material deformation and the finite element simulation study of the material. The flow stress of a material is an important parameter for characterising the material properties during plastic deformation, and is also an important indicator of the physical nature of material deformation [1,2]. Therefore, the selection of a suitable intrinsic structure relationship model can accurately predict. the material flow behaviour and obtain the corresponding flow stresses, providing an important reference for the study of metal plastic deformation theory, the formulation of suitable processing parameters, the control of material properties and finite element simulation [3,4].

Currently, the BP neural network intrinsic structure relationship model has been widely used for the prediction of high-temperature flow stresses in metallic materials due to its ability to quickly and effectively solve complex nonlinear problems with multiple factors [5]. Feng Rui et al [6] predicted the high-temperature flow stress of BT25 titanium alloy based on BP neural network and strain-compensated intrinsic structure model and found that the prediction accuracy of BP neural network intrinsic structure model was higher than that of strain-compensated intrinsic structure model, and the average relative error was only 3,12 %.CAI et al [7] studied the thermal deformation behaviour of 3Cr23Ni8Mn3N based on the BP neural network intrinsic constitutive model and showed that the predicted stress values of the model were in good agreement with the experimental values. However, there are limited studies on the high temperature rheological behavior and intrinsic structure relationship of TC20 titanium alloy by domestic and foreign scholars. Therefore, this paper investigates the high-temperature rheological behaviour of TC20 titanium alloy through hot compression experimental data, and uses BP neural network to establish an intrinsic structure relationship model to accurately predict the high-temperature flow stresses and provide a theoretical basis for the reasonable formulation of plastic forming process of this alloy in actual production.

EXPERIMENTAL MATERIALS AND METHOD

The material used in this experiment was TC20 titanium alloy (Ti-6Al-7Nb) with good strength, plasticity, toughness and strength, the original organisation of which is shown in Figure 1. The isothermal constant strain rate compression experiments were carried out on a Gleeble-1500 thermal simulation tester with a specimen size of Φ 8 mm × 12 mm, deformation temperatures of 750, 800, 850 and 900, strain rates of 0,001,

Z.Y Xuan (E-mail: xuanzhaoyan@ncst.edu.cn), J. L. Miao, College of Mechanical Engineering, North China University of Science and Technology, Hebei, Tangshan, China.

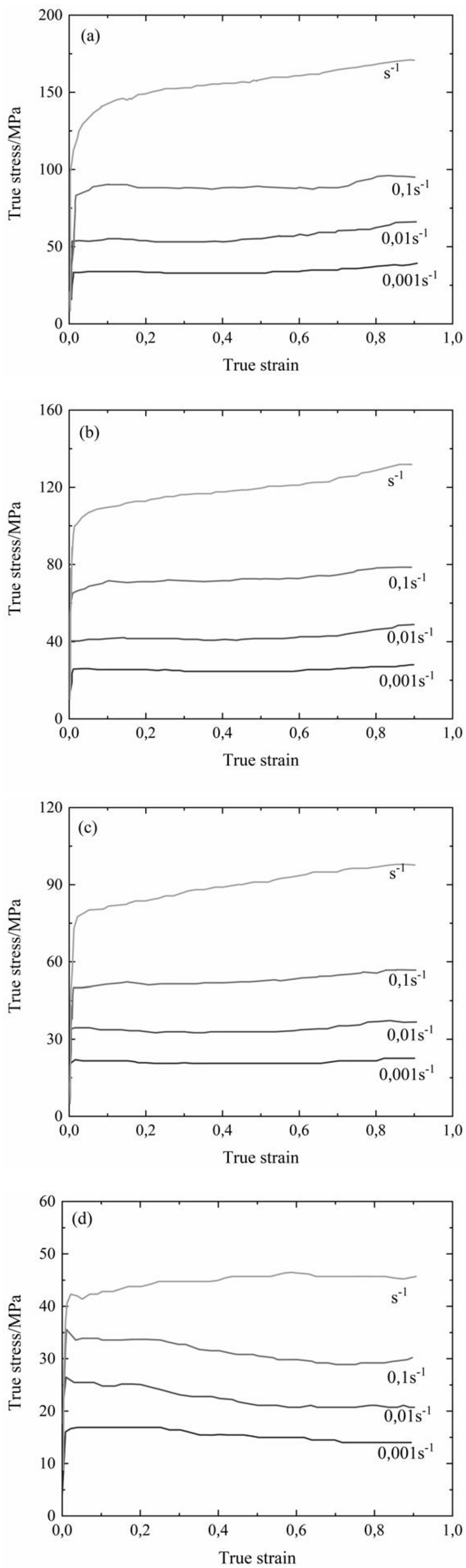

Figure 1 True stress-strain curve for thermal deformation of TC20 titanium alloy (a) 750 °C (b) 800 °C (c) 850 °C (d) 900 °C

0,01, 0,1 and 1 s^{-1} and a 60 % depression rate, and the specimens were heated to the set temperature at a heating rate of 10 °C / s and then held for For 300 s.

TRUE STRESS-STRAIN CURVE

Figure 1 shows the true stress-strain curves of TC20 titanium alloy at different deformation temperatures and different strain rates. It is clear from the graph that the rheological stress of medical TC20 titanium alloy decreases as the deformation temperature increases and the strain rate decreases. Therefore, medical TC20 titanium alloy is a heat-sensitive and strain-rate sensitive material. As the deformation temperature increases, the average kinetic energy of atoms increases and the critical tangential stress for crystal slip decreases, reducing the hindrance of dislocation and intergranular slip. On the other hand, as the deformation temperature increases, dynamic reversion and dynamic recrystallisation are more likely to occur, thereby reducing the dislocation density and counteracting the process hardening that occurs during deformation, thereby contributing to the reduction in rheological stress.

CONSTRUCTION OF A BP NEURAL NETWORK PRINCIPAL STRUCTURE MODEL

BP neural network is a neural network obtained by the error back propagation learning algorithm of multilayer feed-forward network after training, which belongs to forward neural network.Considering the various influencing factors of flow stress and the capability of BP neural network, a 3-layer BP neural network with input layer, implicit layer and output layer was established. The number of neurons in the input layer is set to 3. The number of neurons in the output layer is set to 1, as the output data is the flow stress of TC20 titanium alloy. In general, too many hidden layers will increase the training time and the prediction accuracy is usually not very obvious. In this study, a single hidden layer is used, and the number of neurons in the hidden layer is usually determined according to equation (1).

$$N = \sqrt{n+m} + k \tag{1}$$

Where: N is the number of neurons in the hidden layer; n is the number of neurons in the input layer, n = 3; m is the number of neurons in the output layer, m = 1; k is a constant, $k \in [1,10]$. The structure of the neural network in this study is shown in Figure 2, and the number of neurons in the hidden layer of the neural network can be derived from equation (1) in the range 3 ～ 12. The number of neurons in the hidden layer was selected as 12 after calculation.

In order to ensure the smooth training of the network and the quality of the model, the activation function from the input layer to the hidden layer is the tansig function and the activation function from the hidden layer to the output layer is the purelin function; the learning function

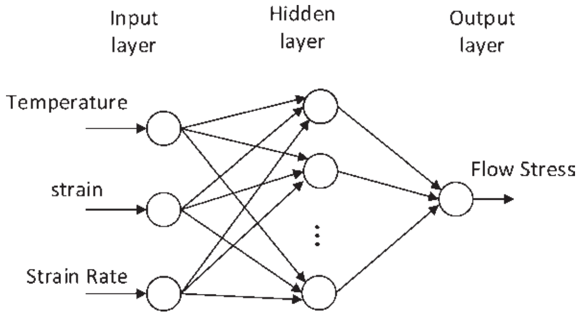

Figure 2 BP neural network structure

is the learngdm function. The learning rate in the range of 0,01 ～ 1. In this study, the learning rate was chosen to be 0.3. The target of the training error was set to 10^{-4} and the number of steps was set to 3 000.

In order to enable the BP neural network to achieve high accuracy and meet the requirements of use, the sample data need to be normalised before input and output. In this paper, the mapminmax function provided in Matlab software is used to normalize the input and output data, and the normalization interval is chosen to be [0,1], and the function expression is shown in equation (2).

$$y = \frac{(y_{max} - y_{min})(x - x_{min})}{x_{max} - x_{min}} + y_{min} \tag{2}$$

Where: y is the normalised value of the input and output data; x is the initial value of the input and output data; x_{max} and x_{min} are the maximum and minimum values of the corresponding input and output data; y_{max} and y_{min} are the maximum and minimum values of the normalised interval.In addition, the normalisation is reversed when the data is output.

$$Y = \frac{(x_{max} - x_{min})(y_0 - y_{min})}{y_{max} - y_{min}} + x_{min} \tag{3}$$

where:Y is the inverse normalised output data; y_0 is the output data normalised in the previous step.

VALIDATION OF BP NEURAL NETWORK INTRINSIC STRUCTURE MODELS

Figure 3 shows a comparison between the predicted values of flow stresses calculated from the BP neural network based intrinsic structure model and the experimental values at different deformation temperatures. Figure 4 shows a plot of the model error analysis. Also in order to measure the accuracy of this intrinsic structure model, the correlation coefficient R (Eq. (4)) and the average relative error AARE (Eq. (5)) are introduced

$$R = \frac{\sum_{i=1}^{N}(E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(E_i - \bar{E})(P_i - \bar{P})^2}} \tag{4}$$

$$AARE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_i - P_i}{E_i}\right| \times 100\% \tag{5}$$

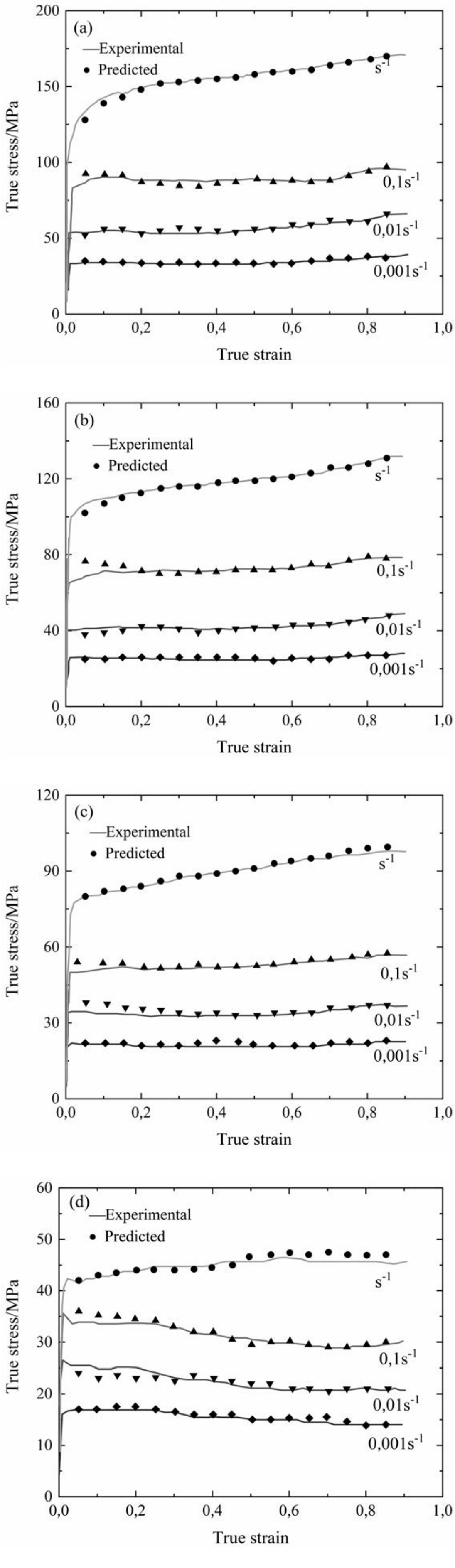

Figure 3 Comparison of experimental and predicted values (a) 750 °C (b) 800 °C (c) 850 °C (d) 900 °C

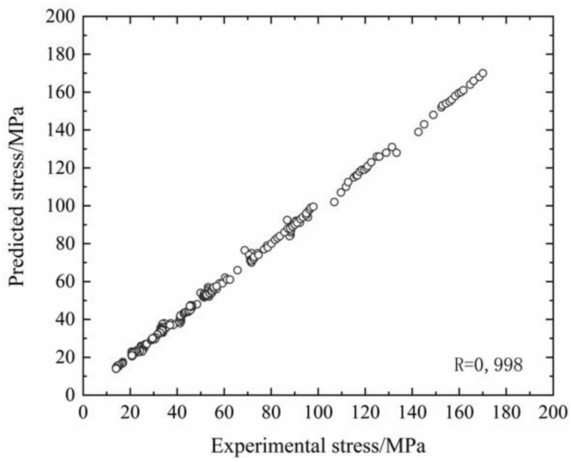

Figure 4 Correlation analysis

where: N is the total number of data; E_i is the experimental value; P_i is the predicted value; $\overline{E}$ is the mean of the experimental values; $\overline{P}$ is the mean of thepredicted value i; E_i is the i-th experimental value; and P_i is the first predicted value.

The correlation coefficient R and the average relative error AARE of the model were 0,998 and 5,06 % respectively when the data were collated and substituted into equation (4) and equation (5), and the deviation value of the predicted value relative to the experimental value was less than 15 % at 95,2 % of the points, indicating that the present structural model has a high prediction accuracy.

CONCLUSION

(1) The flow stress of TC200 titanium alloy is significantly influenced by the deformation temperature and strain rate during the high temperature deformation process. The flow stress basically decreases with increasing deformation temperature and increases with increasing strain rate, and the steady state flow characteristics are more obvious at higher deformation temperatures.

(2) The BP neural network-based intrinsic structure relationship model has high accuracy, its correlation coefficient and average relative error are 0,998 and 5,06 % respectively, which can accurately predict the high temperature flow behaviour, and the results obtained can provide a theoretical basis for the rational formulation of plastic forming process of TC200 titanium alloy for practical production.

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Note: The responsible translator for English language is Y.F. Meng - North China University of Science and Technology, China