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ISSN 0543-5846
METABK 60(3-4) 277-280 (2021)
UDC – UDK 669.295.669…7:620.173.001.4:62.001.57:620.17-536.45:620.16-539.374=111

CONSTITUTIVE RELATIONSHIP OF TC4 TITANIUM ALLOY BASED ON BACK PROPAGATING(BP) NEURAL NETWORK(NN)

Received – Primljeno: 2021-01-14
Accepted – Prihvaćeno: 2021-04-20
Original Scientific Paper – Izvorni znanstveni rad

Using Gleeble-3800 thermal simulation testing machine, the TC4 titanium alloy was subjected to hot compression experiments under the conditions of deformation temperature of 810 – 950 °C, strain rate of 0.001 - 1s^{-1}. The research shows that the flow stress of TC4 titanium alloy is more sensitive to the deformation temperature and strain rate during thermal deformation, and it increases with the decrease of the deformation temperature and the increase of the strain rate. Based on BP neural network, a constitutive model of TC4 titanium alloy α+β two-phase region is established. The correlation coefficient reaches 0,996, which proves that the model can predict the high temperature flow stress of TC4 titanium alloy.

Keywords: TC4 titanium alloy, compression test, constitutive model, BP neural network, stress-strain curve

INTRODUCTION

Titanium alloys have developed rapidly in the field of aerospace due to their high specific strength, strong corrosion resistance, good heat resistance and good low temperature performance. TC4 is the most widely used titanium alloy so far. It is a typical α+β two-phase titanium alloy. Compared with other titanium alloys, it not only has many common advantages of titanium alloys, but also has its own unique excellent quality. Commonly used as various engine blades, casings and other parts [1]. In order to reasonably predict the stress-strain behavior, a large number of scholars have studied TC4 titanium alloy. Wang [2] et al. established a titanium alloy J-C and Arrhenius model through high-temperature tensile tests, and found that the J-C model is more accurate than the Arrhenius model.

Although there are many studies on using the traditional Arrhenius model to predict the stress and strain of TC4 titanium alloy, most of them do not consider the effect of strain [3]. BP neural network is a multi-layer feedforward neural network with powerful self-learning and predictive capabilities [4].

It uses gradient search technology to establish a complex nonlinear model to describe the relationship between the objective function and decision variables. It uses gradient search technology to establish a complex nonlinear model to describe the relationship between the objective function and decision variables, which can effectively reduce the workload of simulation analysis. Lu et al [5] established a constitutive model of BT20 titanium alloy based on neural network, and the study showed that the model can describe the dynamic deformation behavior of BT20 titanium alloy at high temperature. In this paper, through thermal simulation experiments, based on the artificial neural network model, a constitutive model of α+β two-phase region is established for the TC4 titanium alloy, and its applicability is verified. The results can provide theoretical guidance for the actual hot forming of the alloy.

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MATERIALS AND METHODS

The experimental material is TC4 bar produced by Baotai Group. The α+β/β phase transition temperature is about 990 °C. its composition:6,4 %~Al,4,2 %~V,0,024 %~Fe,0,009 %~C,0,004 %~N,0,003 %~H, Matrix~Ti.

Compression test is performed on TC4 on the Gleeble-3800 thermal simulator. The experimental temperature is 810 °C, 880 °C, 950 °C. The strain rate is 0,001s^{-1}, 0,01s^{-1}, 0,1s^{-1}, 1s^{-1}. The experimental process is: heating the sample to the experimental temperature at a rate of 10 °C/s, and compressing it after 3 minutes of holding. The reduction is 60 %.

TRUE STRESS- STRAIN

Figure 1 shows the true stress-true strain curve of TC4 titanium alloy under different deformation conditions.

It can be seen from Figure 1 that when the compression just starts, the stress increases rapidly with the increase of strain, which is caused by work hardening. Then the stress increases slowly with the strain until the peak value, which is caused by the softening behavior caused by the dislocation movement and the competition of work hardening, but at this time the hardening

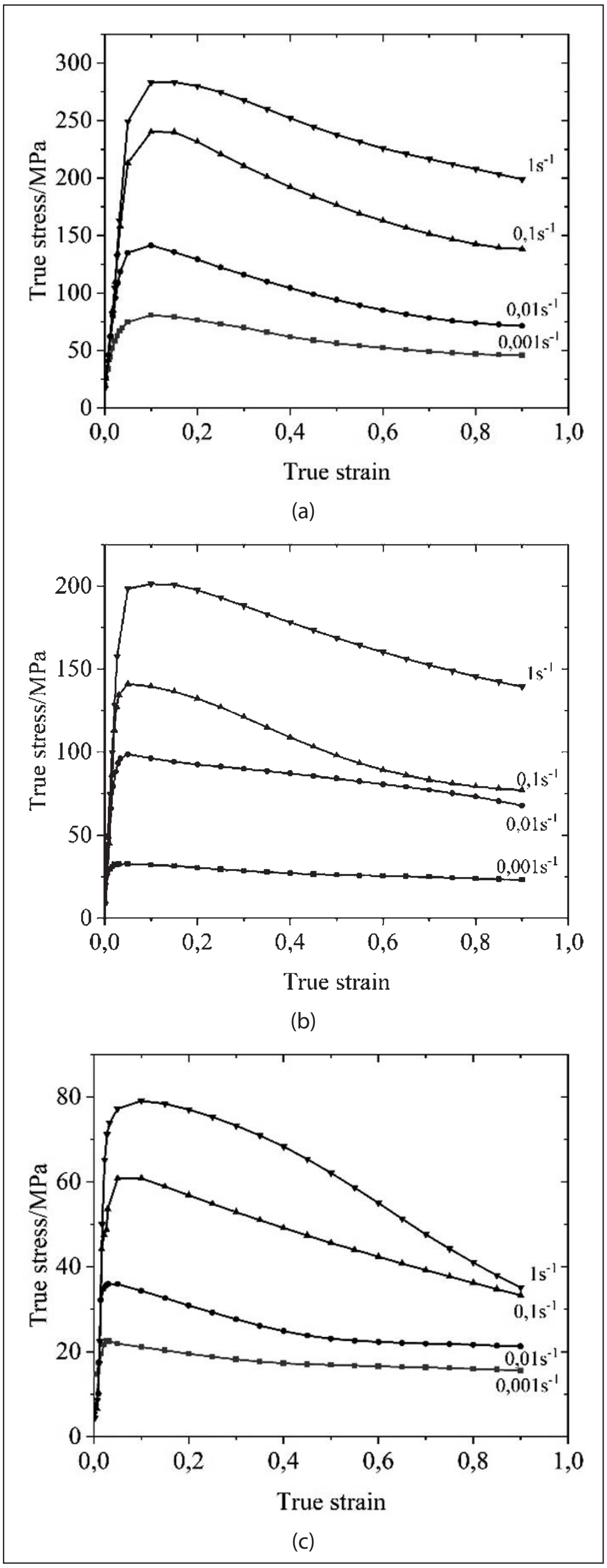

Figure 1 Stress-strain curve under different conditions
(a) 810 °C (b) 880 °C (c) 950 °C

effect is in a dominant position. After the peak stress, the stress decreases slowly with the increase of strain, which is caused by the gradual increase in softening caused by dynamic recrystallization, and the softening is in a dominant position at this time. Finally, the stress reaches a stable value and no longer increases with the increase of strain, and the softening effect and work hardening are balanced. It shows that the flow stress of TC4 titanium alloy is more sensitive to temperature and strain rate. It can also be seen from Figure 1 that with the increase of strain rate at the same temperature, the value of stress also increases continuously. At the same strain rate, as the temperature increases, the value of the stress decreases continuously. It shows that the flow stress of TC4 titanium alloy is more sensitive to temperature and strain rate.

ESTABLISHMENT OF BP CONSTITUTIVE MODEL

In order to more accurately reflect the high temperature deformation characteristics of the TC4 titanium alloy, the constitutive model was established by using BP neural network. In artificial neural network (ANN), the application range of BP neural network is the most common. It can solve a variety of complex nonlinear problems without the need for a predetermined model. The BP algorithm also has a certain degree of association fault tolerance, which can be achieved through the mapping relationship between thermal deformation parameters and flow stress. Look for general rules in a large amount of experimental data, and match the model that fits the experimental data through the threshold and weight of the training target [6].

In this study, the BP neural network includes three layers: input layer, output layer and hidden layer. The input layer is composed of three units of deformation temperature, strain rate and strain, and the output layer has only one neuron of stress. Theoretically speaking, for comprehensive consideration, the general selection of the number of hidden layers is: $\sqrt{m+n+a}$. a is a constant between 0 and 10. m and n are the number of input and output neurons respectively. This paper compares the parameter values of the mean square error of the network when the hidden layer and the hidden layer unit take different numbers. According to the principle of minimum error, the structure of the BP network is determined to be 3 × 6 × 7 × 1. The structure diagram is shown in Figure 2.

In this study, 204 sets of input and output data are selected from the experimental data with experimental deformation temperature of 810 – 950 °C, strain rate of 0,001 ~ $1s^{-1}$, and true strain of 0,1 ~ 0,9 (true strain interval 0,05). Among them, 102 sets of data are used to train the prediction model, and the other 102 sets of data are used to predict the accuracy of the model. The specific grouping situation is shown in Table 1. Where C is the training sample and T is the test sample. In BP neural network, Sigmoid differentiable function and linear function are usually used as the activation function of the network. In this paper, the sigmoid tangent function tansig is selected as the activation function of hidden layer neurons. The transfer function from the hidden layer to the output layer is a purelin function. Assuming

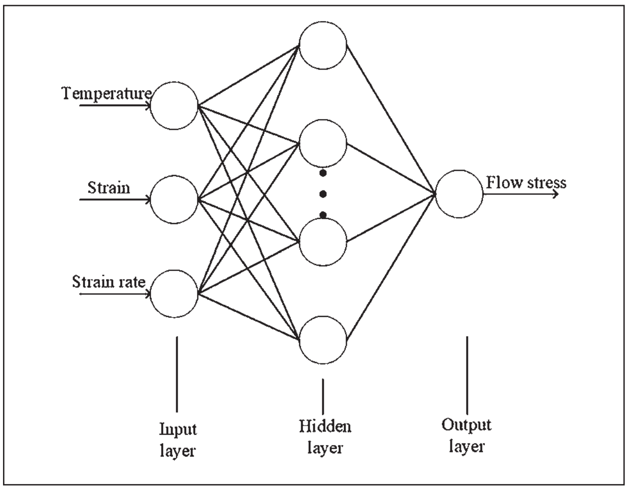

Figure 2 Schematic diagram of BP neural network model

that the output of the j-th training sample unit f from the input layer to the output layer i *O(jf)*:

$$O\left(jf\right) = net\left(jf\right) = \frac{1}{1 + \exp[-(\sum W_{jf} X_f + \theta_f)]} \quad (1)$$

In the equation (1): *net(jf)* is the input of the f-th neuron in the hidden layer; W_{jf} is the weight between the input layer and the hidden layer; X_f is the input of the f - th neuron in the hidden layer to the hidden layer; $_f$ is the threshold from the input layer to the output layer.

Table 1 **TC4 titanium alloy training data and test data grouping**

Strain rate /s^{-1}	Deformation temperature / °C		
	810	880	950
0,001	T	C	T
0,01	C	T	C
0,1	T	C	T
1	C	T	C

Because the components of the input layer have large differences in value, the accuracy of the model is low. Therefore, for the purpose of focusing the data on one or more neurons, the input data must be standardized. Generally, equation (2) is usually used to normalize T and σ [7].

$$Y = \frac{X - 0{,}95X_{min}}{1{,}05X_{max} - 0{,}95X_{min}} \quad (2)$$

In the equation (2): X is the experimental data, X_{min},X_{max} is the extreme value of X, and Y is the normalized value.

$\dot{\varepsilon}$ is usually normalized by equation (3):

$$\dot{\varepsilon} = \frac{3 + ln\dot{\varepsilon} - 0{,}95(3 + ln\dot{\varepsilon}_{min})}{1{,}05\left(3 + ln\dot{\varepsilon}_{max}\right) - 0{,}95(3 + ln\dot{\varepsilon}_{min})} \quad (3)$$

The maximum number of iterations of the BP neural network is set to 3000, the momentum factor is 0,9, the learning rate is 0,3, the target error is 10^{-3}, the learning factor is set to 1,5, and the maximum number of iteration steps is 100. Finally, the BP model can be calculated by substituting the data.

VALIDATION OF BP CONSTITUTIVE MODEL

Figure 3 shows the training results. After 26 iterations, the training results reached the error target, the established model quickly converged, and the training was completed.

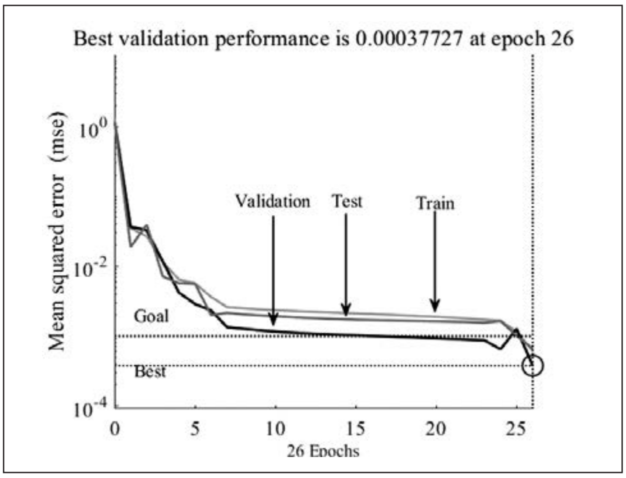

Figure 3 Training convergence curve

Figure 4 shows the comparison between the predicted value of and the experimental value of the TC4 titanium.

The correlation coefficient R is used to describe the accuracy of the BP neural network model, and the result is shown in Figure 5. The correlation coefficient R is 0,996. It is proved that the experimental value and the predicted value are in high agreement.

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

In the equation (4): E_i is the experimental flow stress value (MPa); $\overline{E}$ is the average value of experimental flow stress (MPa); P_i is the predicted flow stress value (MPa); $\overline{P}$ is the predicted mean flow stress(MPa); N is the number of data.

CONCLUSION

The flow stress of TC4 titanium alloy is more sensitive to the deformation temperature and strain rate during thermal deformation, and it increases with the decrease of the deformation temperature and the increase of the strain rate.

Established a BP neural network model of TC4 titanium alloy. its correlation coefficient R is 0,996, and the predicted value is highly consistent with the experimental value. It shows that this model can predict the rheological behavior of TC4 titanium alloy under different strains.

Acknowledgments

This work is supported by the Tangshan talent foundation innovation team (201 302 04D).

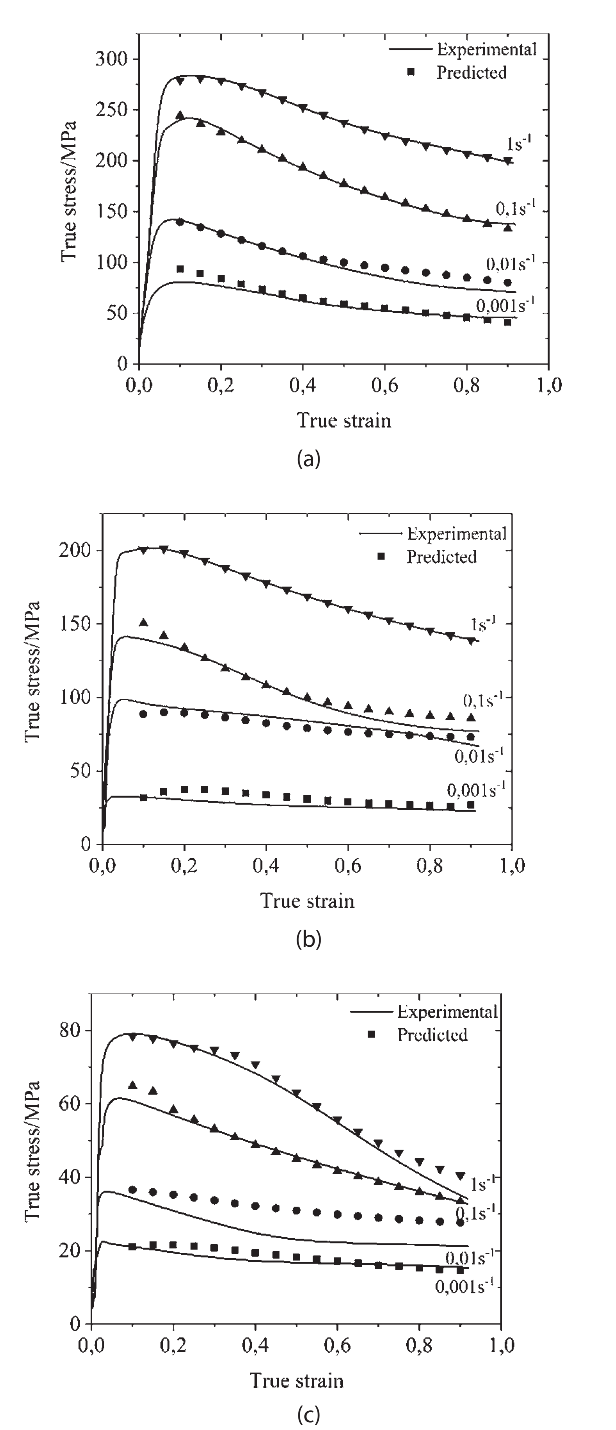

Figure 4 Comparison of experimental value and predicted value (a) 810 °C (b) 880 °C (c) 950 °C

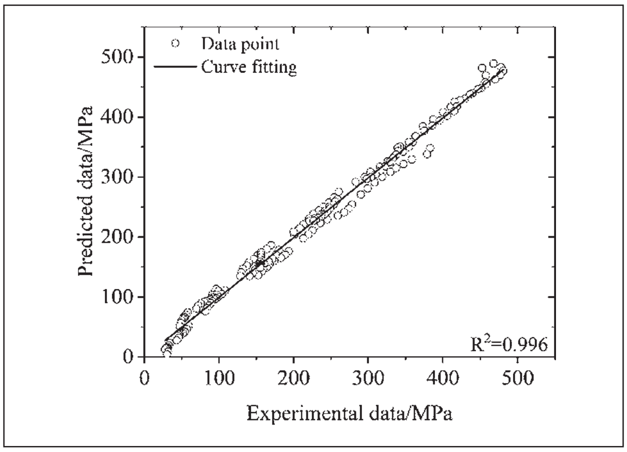

Figure 5 Correlation analysis

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Note: The responsible translator for English language is Z. Ma. North China University of Science and Technology, China