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A Characterization of Hot Flow Behaviors Involving Different Softening Mechanisms by ANN for As-Forged Ti-10V-2Fe-3Al Alloy

Abstract: The isothermal compressions of as-forged Ti-10V-2Fe-3Al alloy at the deformation temperature range of 948–1,123 K and the strain rates in the range of 0.001–10 s⁻¹ with a height reduction of 60% were conducted on a Gleeble-3500 thermo-mechanical simulator. The flow behaviors show nonlinear sensitivity to strain, strain rate and temperature. Based on the experimental data, an artificial neural network (ANN) with back-propagation algorithm was developed to deal with the complex deformation behavior characteristics. In the present ANN model, strain, strain rate and temperature were taken as inputs, and flow stress as output. A comparative study on the constitutive relationships based on regression and ANN methods was conducted. According to the predicted and experimental results, the predictabilities of the two models have been evaluated in terms of correlation coefficient (*R*) and average absolute relative error (AARE). The *R*-value and the AARE-value at strain of 0.5 from the ANN model is 0.9998 and 0.572%, respectively, better than 0.9902 and 6.583% from the regression model. The predicted strain–stress curves outside of experimental conditions indicate similar characteristics with experimental curves. The results have sufficiently articulated that the well-trained ANN model with back-propagation algorithm has excellent capability to deal with the complex flow behaviors of as-forged Ti-10V-2Fe-3Al alloy.

Keywords: Ti-10V-2Fe-3Al titanium alloy, flow stress, constitutive model, artificial neural network

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Introduction

As a typical metastable β titanium alloy, Ti-10V-2Fe-3Al alloy is especially attractive for aircraft structural components on account of superior mechanical properties such as high specific strength, excellent fracture toughness and good corrosion resistance [1–3]. It is well known that the hot deformation behaviors of titanium alloy are sensitively dependent on deformation parameters involving strain, strain rate and temperature. In the course of plastic deformation under various conditions, several metallurgical phenomena including work hardening (WH), dynamic recrystallization (DRX) and dynamic recovery (DRV) coexist with one being predominant. WH increases the flow stress in deformation processes and reduces the plasticity of materials, while work softening mechanism like DRX or DRV decreases the flow stress and increases the plasticity of materials. In a wide temperature range across β -transus, the interaction of different metallurgical phenomena induces the highly nonlinear flow behaviors and their complex evolutions which are all indicated in the stress–strain curves at different conditions. Therefore, the constitutive relationships between flow stress and processing parameters contribute significantly to the deep understanding of flow behaviors and even further optimization of hot deformation process [4].

At present, two types of constitutive models, namely analytical and phenomenological models, are in vogue for analyzing hot flow behaviors of materials [5]. Closely connected with physical theories, the analytical model is obtained through a very clear and deep understanding of flow behaviors and deformation mechanisms of metallic materials based on a large amount of experimental data, making it difficult to model the constitutive relationships under limited experimental conditions. However, the phenomenological model, which is less rigorously related to physical theories in comparison with the analytical model, is widely adopted in practice for effective modeling of flow behaviors. Typical phenomenological approaches are using regression method to conduct the constitutive equations, including the Arrhenius-type constitutive

equations based on exponential law, power exponential law and hyperbolic sine law [6], in which only a reasonable number of material constants need to be calculated through regression analysis with a limited amount of experimental data. However, these phenomenological models are not quite satisfied due to the low accuracy in predicting the highly nonlinear constitutive relationships of the metallic materials in a very large parameter range. Besides, the poor flexibility of these models also induces a loss of accuracy in flow stress prediction outside the experimental conditions [7].

Compared with the regression method, the artificial neural network (ANN), as a relatively new artificial intelligence technique, is able to solve the complex nonlinear problems well by means of simulating the behavior of biological neural systems in computers [8]. This approach makes it possible to deal with the constitutive relationships of the flow stress, strain, strain rate and temperature with a collection of representative examples from the desired mapping functions for training instead of a well-defined mathematical model [9–11]. As a consequence, the flow stress can be predicted through the constitutive model obtained by ANN method. For the past few decades, the description of constitutive relationships by ANN method has attracted many researchers. Quan et al. developed an ANN constitutive model of as-cast Ti-6Al-2Zr-1Mo-1V alloy in a wide temperature range involving phase transformation [8] and predicted the high-temperature flow behavior of 20MnNiMo alloy using ANN [12]. Peng et al. compared the constitutive relationships of as-cast Ti60 titanium alloy based on Arrhenius-type and ANN model [13]. Zhu et al. successfully constructed an ANN model to predict the flow stress of as-cast TC21 titanium alloy [6]. The results of stress prediction in these researches agree well with the experimental data, indicating that the ANN is an effective tool available to model the highly nonlinear constitutive relationships of metallic materials.

Aiming at developing an ANN model to predict the flow stress of as-forged Ti-10V-2Fe-3Al titanium alloy using back-propagation (BP) algorithm, 40 compression tests were conducted in a wide range of temperatures and strain rates in the present work to study the flow behavior of as-forged Ti-10V-2Fe-3Al alloy. The strain–stress data collected in the compression tests were then employed to develop the ANN model and to determine the constants of the constitutive model by regression method. Subsequently, a comparative analysis to evaluate the two models has been performed based on standard statistical parameters. Higher correlation coefficient (R) and lower average absolute relative error (AARE) than the constitutive model by regression method indicate that the ANN model has excellent accuracy to fit the experimental data in a wide range of temperature and strain rate, and it is a good approach to model the flow behaviors of as-forged Ti-10V-2Fe-3Al alloy.

Materials and experimental procedure

The chemical compositions (wt.%) of as-forged Ti-10V-2Fe-3Al alloy used in the current investigation are as follows: V-10, Fe-1.9, Al-3.0, Si-0.05, C-0.05, N-0.05, H-0.0125, O-0.13, Ti (balance). The β -transus temperature of the alloy is about $1,068 \pm 5$ K. The as-forged Ti-10V-2Fe-3Al alloy employed was provided in the form of bar with the diameter of 180 mm. The original microstructure of as-forged Ti-10V-2Fe-3Al alloy is shown in Figure 1. A typical acicular microstructure can be markedly observed, in which acicular α -phase grains are dispersed in the matrix of large β -phase grains. The following experimental procedures are according to ASTM E209-00 Standard. The specimen for isothermal compression test was a cylinder 10 mm in diameter and 12 mm in height,

Figure 1 Initial microstructures of as-forged Ti-10V-2Fe-3Al alloy

and 40 such specimens were machined with their cylinder axes parallel to the axial line direction of the bar. All the specimens were homogenized under a temperature of 1,033 K for 1 hour. The isothermal compression tests were conducted on a Gleeble-3500 thermo-mechanical simulator. In this experiment, all the specimens were resistance heated to the deformation temperature at a heating rate of 10 K/s and held at that temperature for 150 s by thermo-coupled-feedback-controlled AC current. All the specimens were compressed to a true strain of 0.9 (height reduction of 60%) at eight different temperatures of 948 K, 973 K, 998 K, 1,023 K, 1,048 K, 1,073 K, 1,098 K and 1,123 K, and five different strain rates of 0.001 s^{-1} , 0.01 s^{-1} , 0.1 s^{-1} , 1 s^{-1} and 10 s^{-1} . After each compression, the deformed specimen was rapidly water-quenched to retain the recrystallized microstructures.

The variations of stress and strain were monitored continuously by a personal computer equipped with an automatic data acquisition system during the compression process. However, when the strain reaches a certain value, uneven deformation will occur to specimens, which will change the constant strain rate state. Therefore, the original unidirectional stress state changes into a complex three-dimensional stress state, which will violate the authenticity of deformation. If uneven deformation occurs to the specimens after compression, dilatation coefficient B can be used to measure validity of the compression tests according to the judgment standard of physics laboratory in the UK. That is, $B = L_0 d_0^2 / L_f d_f^2$, where B is dilatation coefficient, L_0 is specimen's original height, d_0 is specimen's original diameter, L_f is specimens' average height after compression and d_f is specimens' average diameter after compression. When $B \geq 0.9$, the results of the compression tests are considered effective. However, when $B \leq 0.9$, correction computation is needed as $\sigma_i = 4F_i / \pi d_i^2 (1 + (\mu d_i / 3L_i))$, where σ_i is true stress, F_i , d_i and L_i are instantaneous pressure, specimens' average diameter and height; μ is friction coefficient. After the compression tests, all the specimens' dilatation coefficient is validated, $B > 0.9$, namely the results of the compression tests are effective and need no correction.

The true stress and true strain were derived from the measurement of the nominal stress-strain relationships according to the following formula: $\sigma_T = \sigma_N(1 + \varepsilon_N)$, $\varepsilon_T = \ln(1 + \varepsilon_N)$, where σ_T is true stress, σ_N is nominal stress, ε_T is true strain and ε_N is nominal strain [14]. The true compressive stress-strain curves of as-forged Ti-10V-2Fe-3Al alloy recorded automatically in the isothermal compression process are shown in Figure 2(a)–2(h), which in turn would be used for the development of the ANN model.

Flow behavior characteristics of as-forged Ti-10V-2Fe-3Al alloy

True stress-strain curves

As shown in Figure 2, the flow stress as well as the shape of the flow curves of as-forged Ti-10V-2Fe-3Al alloy is sensitively dependent on temperature and strain rate. The stress-strain curve articulates the intrinsic characteristics of flow stress with thermodynamic softening behaviors. It can be summarized from all the true stress-strain curves that there are three distinct stages in the stress evolution with strain. At the first stage where WH predominates, the flow stress increases rapidly to a critical value. Then the flow stress increases lesser and lesser until a peak value or an inflection of work-hardening rate at the second stage, indicating that the work softening due to DRX and DRV becomes more and more predominant, then it exceeds WH. At the final stage, it can be summarized that two types of curve variation tendency exist: in the parameter domains of 948–1,023 K where α -phase and β -phase coexist, the flow stress decreases continuously with strain due to obvious DRX softening; however, in the parameter domains of 1,048–1,123 K where β -phase predominates, the variation of flow stress with strain becomes almost smooth and appears to be a steady-state characteristic with significant DRV softening.

Thermal activation process for hot deformation

During hot deformation process, it is very widely known that the constitutive relationships between the steady-state flow stress, strain rate and deformation temperature are represented by Zener-Hollomon parameter, in an exponent-type equation, and the hyperbolic law in the Arrhenius-type equation gives better approximations between Z parameter and stress, as expressed in eq. (1) [15–18]:

$$Z = \dot{\varepsilon} \exp\left(\frac{Q}{RT}\right) = AF(\sigma) \quad (1)$$

where

$$F(\sigma) = \begin{cases} \sigma^m & \alpha\sigma < 0.8 \\ \exp(\beta\sigma) & \alpha\sigma < 1.2 \\ [\sinh(\alpha\sigma)]^n & \text{for all } \sigma \end{cases}$$

in which $\dot{\varepsilon}$ is the strain rate (s^{-1}), R is the universal gas constant ($8.31 \text{ J mol}^{-1} \text{ K}^{-1}$), T is the absolute temperature (K),

Figure 2 The true stress–strain curves of as-forged Ti-10V-2Fe-3Al alloy under the different strain rates with temperatures of (a) 948 K, (b) 973 K, (c) 998 K, (d) 1,023 K, (e) 1,048 K, (f) 1,073 K, (g) 1,098 K, (h) 1,123 K

Q is the apparent activation energy for hot deformation (kJ mol^{-1}), σ is the flow stress (MPa) for a given strain, A , α , m and n are the material constants, $\alpha = \beta/n$.

In the current study, the experimental datasets involving deformation temperature, strain rate and peak stress (σ_P) at peak strain were fitted into eq. (1). The relationships between $\ln \dot{\epsilon} - \ln \sigma_P$, $\ln \dot{\epsilon} - \sigma_P$, $\ln \dot{\epsilon} - \ln[\sinh(\alpha\sigma_P)]$ and $\ln[\sinh(\alpha\sigma_P)] - 10,000/T$ in $\alpha + \beta$ -phase temperature range are shown in Figure 3. The value of m and β was obtained through taking average slope of the lines in Figure 3(a) and 3(b), respectively. Thus the α -value in $\alpha + \beta$ -phase temperature range was calculated to be 0.005195. Subsequently, the calculation of n and Q has been performed according to the following relationships:

$$Q = Rns \quad (2)$$

$$n = \frac{d \ln \dot{\epsilon}}{d \ln[\sinh(\alpha\sigma)]} \quad (3)$$

$$s = \frac{d \ln[\sinh(\alpha\sigma)]}{d(1/T)} \quad (4)$$

Hence the value of n and Q in $\alpha + \beta$ -phase temperature range was calculated to be 4.1972 and 463.09 kJ/mol, respectively, from the slope of the lines in Figure 3(c) and 3(d). In the same way, the value of α , n and Q in β -phase temperature range was calculated to be 0.010199, 3.2812 and 210.45 kJ/mol, respectively, from the plots of $\ln \dot{\epsilon} - \ln \sigma_P$, $\ln \dot{\epsilon} - \sigma_P$, $\ln \dot{\epsilon} - \ln[\sinh(\alpha\sigma_P)]$ and $\ln[\sinh(\alpha\sigma_P)] - 10,000/T$ in β -phase temperature range, as shown in Figure 4.

The hot deformation behaviors are influenced by the process of thermal activation, and the softening mechanism is related to the thermal activation energy (Q), whose value reflects the difficulty of the dislocation moving, DRV and DRX. Many researchers have revealed that the self-diffusion activation energy of α -Ti in pure titanium is in the range of 169–242 kJ/mol, while the self-diffusion activation energy of β -Ti is 153–166 kJ/mol. As mentioned earlier, the activation energy for hot deformation in $\alpha + \beta$ -phase temperature range is determined to be 463.09 kJ/mol, which is much larger than the activation energy of self-diffusion. However, the calculated Q -value (210.45 kJ/mol) in β -phase temperature range is almost

Figure 3 Relationships between (a) $\ln \dot{\epsilon} - \ln \sigma_P$, (b) $\ln \dot{\epsilon} - \sigma_P$, (c) $\ln \dot{\epsilon} - \ln[\sinh(\alpha\sigma_P)]$, (d) $\ln[\sinh(\alpha\sigma_P)] - 10,000/T$ in $\alpha + \beta$ -phase temperature range

Figure 4 Relationship between (a) $\ln \dot{\epsilon} - \ln \sigma_P$, (b) $\ln \dot{\epsilon} - \sigma_P$, (c) $\ln \dot{\epsilon} - \ln(\sinh(\alpha \sigma_P))$, (d) $\ln(\sinh(\alpha \sigma_P)) - 10,000/T$ in β -phase temperature range

equal to the self-diffusion activation energy of β -Ti. In general, the DRV predominates in the work softening process of hot deformation when the activation energy for hot deformation did not appear to be much different from the self-diffusion activation energy, while the DRX is the main softening mechanism when the activation energy for hot deformation is much larger than the self-diffusion activation energy.

The variation of activation energies for as-forged Ti-10V-2Fe-3Al alloy in hot deformation along with the increase of strain from 0.02 to 0.8 is shown in Figure 5. It is obviously seen from Figure 5 that the activation energy for hot deformation decreases with strain increases in β -phase temperature range, reflecting that the energy for deformation decreases with the increase of the plastic deformation. The average activation energy for hot deformation in β -phase temperature range was calculated from Figure 4 to be 188.71 kJ/mol. It is almost equal to the self-diffusion activation energy of 166 kJ/mol for β -Ti, indicating that the DRV predominates in the work softening process of as-forged Ti-10V-2Fe-3Al alloy in β -phase temperature range. This can be proved in

Figure 5 The relationship between Q and strain

Figure 2, as the variation of flow stress with strain in β -phase temperature range appears to be a steady-state characteristic with significant DRV softening.

However, in $\alpha + \beta$ -phase temperature range, when the strain increases, the activation energy for hot deformation increases rapidly to a peak value and then decreases gradually to a relatively low level, as shown in Figure 5. Meanwhile, it can also be seen in Figure 5

Figure 6 The microstructure of as-forged Ti-10V-2Fe-3Al alloy at different deformation conditions

that the activation energy for hot deformation in $\alpha + \beta$ -phase temperature range is much larger than the self-diffusion activation energies of α -Ti (242 kJ/mol) and β -Ti (166 kJ/mol), which means that the DRX predominates in softening mechanism during hot deformation of as-forged Ti-10V-2Fe-3Al alloy. Figure 6 shows the typical microstructure of as-forged Ti-10V-2Fe-3Al alloy at different deformation conditions in $\alpha + \beta$ -phase temperature range. It can be seen from Figure 6 that the α -phase grains are fined by globularization which can be regarded as a type of DRX, and the matrix of β -phase is surrounded by equiaxed α -phase grains. In fact, when the specimen is compressed, it is significantly difficult to identify the grain boundaries of β -phase due to the crush, globularization and confusion of aciculate α -phase grains in the grain boundaries of β -phase.

It indicates that for as-forged Ti-10V-2Fe-3Al the softening mechanism transforms from DRX to DRV with increasing temperature, which is due to an allotropic phase transformation from α -phase to β -phase. As a result, the extremely complex flow behaviors of as-forged Ti-10V-2Fe-3Al in a wide temperature range make it difficult to predict the flow stresses during hot deformation with constitutive models by regression method, whereas the ANN is able to deal with the highly nonlinear relationships well.

Development of ANN model for as-forged Ti-10V-2Fe-3Al

ANN model

ANN, as a kind of computational model of biological neuron, is able to generalize the deformation behavior

characteristics by simulating the working process of biological neurons with network structures, making it possible to build a constitutive model with high precision. The typical structure of an ANN consists of one input layer, one output layer and one or more hidden layers. These layers are connected by the fundamental units of ANN named artificial neurons with a function of taking a weighted sum of the inputs. The hidden layer works as a complex network architecture to simulate the complex nonlinear relationships between outside information received in input layer and output information generated from output layer [6, 9, 19, 20]. Among the various kinds of ANNs available, the multilayer feed-forward ANN with BP algorithm is becoming increasingly popular in materials modeling. The training of feed-forward ANN in this work is undertaken using BP algorithm to get a better understanding of the constitutive relationships between the inputs and outputs since it is a typical means of adjusting the weights and biases by utilizing gradient descent to minimize the target error [21] and has a great representational power for dealing with highly nonlinear and strongly coupled relationship [22].

In this investigation, the input variables of ANN contain deformation temperature (T), strain (ε) and strain rate ($\dot{\varepsilon}$), while the output variable is flow stress (σ). Thus, a feed-forward network with BP algorithm was developed, as shown in Figure 7. In the present study, 1,600 normalized datasets have been selected from the 40 stress-strain curves. When developing the ANN model, the datasets at a strain of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.8 were chosen as the testing sets, while the available datasets remaining were used to train the model. The experimental data containing temperature, strain, strain rate and stress were measured in different units, leading to the decrease of the convergence speed

Figure 7 Schematic illustration of the neural network architecture

and accuracy of the model. As a result, the input and output variables should be normalized into dimensionless units before training to reduce the effects caused by different units. From the stress-strain curves shown in Figure 2, it can be seen that the input strain data vary from 0.02 to 0.8, strain rate data vary from 0.001 s^{-1} to 10 s^{-1} , temperature data vary from 948 K to 1,123 K and the output flow stress data vary from 23.93 MPa to 587.45 MPa. The temperature data, strain data and the flow stress data were normalized within the range from 0.05 to 0.3 using the relation given by eq. (5). Meanwhile, the strain rate data, after taking logarithm of the values, were normalized using the relation given by E. (6), since the range of the data is much too wide:

$$y_n = 0.05 + 0.25 \frac{y - 0.95y_{\min}}{1.05y_{\max} - 0.95y_{\min}} \quad (5)$$

$$y_n = 0.05 + 0.25 \frac{(4 + y) - 0.95(4 + y_{\min})}{1.05(4 + y_{\max}) - 0.95(4 + y_{\min})} \quad (6)$$

where y_n is the normalized value of y , y is the experimental data, $y_{\max}$ and $y_{\min}$ are the maximum and minimum value of y , respectively.

The structural parameters, involving hidden layer number, transfer function, training function and neuron number for each hidden layer, are of great significance for an excellent ANN model. Firstly, two hidden layers were adopted in the current investigation to ensure high accuracy. Subsequently, an associated transfer function, which can represent how the weighted sum of its inputs is transferred to the results into outputs, was set for each layer. The selected transfer function is “tan sigmoid” for each hidden layer, and “pure linear” for output layer. In addition, the training function is “trainbr.” Finally, the neuron number for each hidden layer was set by means of trail-and-error method according to the experience of designers and the training sample size. If the neuron number of each hidden layer in the ANN model is too

small, the model may be insufficient to learn the process correctly when in training. On the contrary, too many neurons may slow the convergence rates or over-fit the data. The ANN model in the current investigation was trained firstly with three neurons in each hidden layer, and then the neuron number was adjusted continually (from 3 to 21) for the purpose of approaching the expected accuracy.

Evaluation of the performance of training work

The value of mean square error (MSE), expressed by eq. (7). [23], is introduced to evaluate the ability of the ANN training work and determine the neuron number for each hidden layer:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (E_i - P_i)^2 \quad (7)$$

where E is the sample of experimental value, P is the sample of predicted value by ANN model and N is the number of strain-stress samples.

The MSE-value of each actual training work was calculated as the training work of ANN models with different neuron numbers was accomplished. It is obviously seen in Figure 8 that the MSE decreases to the minimum value when the neuron number in each hidden layer is 18, showing that the ANN model with 18 neurons in each hidden layer exhibits optimal performance.

The generalization performance of the well-trained ANN model is measured in terms of R and the AARE [23–26], as expressed by eqs (8) and (9), respectively.

Figure 8 Performance of the network at different hidden neuron levels

R is a widely used evaluator to measure the strength of linear relationships between experimental and predicted values, while the AARE indicates the accuracy of the prediction.

$$R = \frac{\sum_{i=1}^N (E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^N (E_i - \bar{E})^2 \sum_{i=1}^N (P_i - \bar{P})^2}} \quad (8)$$

$$\text{AARE}(\%) = \frac{1}{N} \sum_{i=1}^N \left| \frac{E_i - P_i}{E_i} \right| \times 100 \quad (9)$$

where E is the sample of experimental value, P is the sample of predicted value by ANN model, $\bar{E}$ and $\bar{P}$ are the mean value of E and P , respectively, N is the number of strain–stress samples.

High levels of R -values and low levels of AARE-values indicate that the predicted flow stress values agree very well with the experimental value. As shown in Figure 9, R was linearly fitted with a value of 0.9999, and the AARE is calculated to be a determined percent of 0.402%, showing a good correlation between experimental and predicted flow stress values by the ANN model with 1,280 training datasets in total. As a result, the well-trained ANN model has excellent accuracy and is able to predict the flow behaviors of as-forged Ti-10V-2Fe-3Al alloy well.

In order to check the prediction ability, the ANN model is tested by the testing datasets involving datasets at strain of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.8, which were not used in the training work. Figure 10(a) and 10(b) shows the correlation relationships between predicted flow stress values by ANN model and experimental values in testing procedure for the $\alpha + \beta$ -phase

Figure 9 Correlation between experimental and predicted flow stress for the training datasets

temperature range and β -phase temperature range, respectively. As shown in Figure 10, in the $\alpha + \beta$ -phase temperature range where temperature is lower than 1,068 K, the R -value and the AARE-value are calculated to be 0.99981 and 0.576%, respectively, as well as the 0.99984 and the 0.691% for the β -phase temperature range where temperature is higher than 1,068 K, illustrating that the accuracy has been achieved to the ideal level.

As the well-trained ANN model has achieved excellent accuracy, it can be adopted to predict the flow stress in a wide range of temperature, strain and strain rate. Figure 11 shows the comparisons between the datasets predicted by ANN model and the strain–stress curves obtained from compression tests. It is obviously seen in Figure 11 that the predicted datasets fit the experimental curves well in a

Figure 10 Correlations between experimental and predicted flow stress in testing procedure for (a) $\alpha + \beta$ -phase temperature range, (b) β -phase temperature range

Figure 11 Comparison between the experimental and predicted flow stress by ANN model at different strain rates and temperatures: (a) 948 K, (b) 973 K, (c) 998 K, (d) 1,023 K, (e) 1,048 K, (f) 1,073 K, (g) 1,098 K, (h) 1,123 K

wide temperature range of 948–1,123 K, a wide strain rate range of $0.001\text{--}10\text{ s}^{-1}$ and a wide strain range of $0.1\text{--}0.8$, no matter what the softening mechanism is and whether or not the phase transformation occurs.

Comparison of constitutive model by regression method and ANN model for as-forged Ti-10V-2Fe-3Al

Constitutive model by regression method for as-forged Ti-10V-2Fe-3Al alloy

The constitutive model for as-forged Ti-10V-2Fe-3Al alloy was obtained in the form of eq. (1) through non-linear multivariate regression analysis similar to the

method in Chapter 3 with datasets involving deformation temperature, strain rate and stress at the strain of 0.5.

The relationships between $\ln \dot{\epsilon} - \ln \sigma$, $\ln \dot{\epsilon} - \sigma$, $\ln \dot{\epsilon} - \ln[\sinh(\alpha\sigma)]$ and $\ln[\sinh(\alpha\sigma)] - 10,000/T$ are shown in Figure 12. Hence the value of α , n and Q was calculated to be 0.008065, 3.759 and 214.16 kJ/mol, respectively. The value of A was then obtained to be 2.295×10^9 from the intercept of the fitted line in Figure 13. Finally, the constitutive equation by regression method can be presented as eq. (10):

$$Z = \dot{\epsilon} \exp\left(\frac{214.16}{RT}\right) = 2.295 \times 10^9 [\sinh(0.008065\sigma)]^{3.759} \quad (10)$$

Nevertheless, it is very difficult to calculate a set of equation parameters for the whole strain range to deal

Figure 12 Relationships between (a) $\ln \dot{\epsilon} - \ln \sigma$, (b) $\ln \dot{\epsilon} - \sigma$, (c) $\ln \dot{\epsilon} - \ln(\sinh(\alpha\sigma))$, (d) $\ln(\sinh(\alpha\sigma)) - 10,000/T$ at strain of 0.5

Figure 13 Variation of the Z parameter with flow stress (at strain of 0.5)

with the specific deformation characteristics. On the contrary, the ANN model is able to figure out this problem.

Comparison of the performance of the two models

Figures 14 and 15 show the correlation relationships between the experimental and predicted data at the strain of 0.5 from the well-trained ANN model and the regression model, respectively. The R -value and the AARE-value calculated from the ANN model are 0.9998 and 0.572%, respectively, better than the 0.9902 and 6.583% from the regression method, respectively, indicating that the ANN model has better capacity to predict the flow behaviors of as-forged Ti-10V-2Fe-3Al alloy.

Additionally, as expressed by eq. (11), the relative percentage error (η) is introduced to compare various measurements of the relative difference at strain of 0.5, besides R and the AARE.

$$\eta(\%) = \frac{P_i - E_i}{E_i} \times 100\% \quad (11)$$

Figure 14 Correlation between experimental and predicted flow stress by ANN model at strain of 0.5

Figure 16 Comparison of relative percent error of predicted value by ANN and calculated value by regression model with experimental value at strain of 0.5

Figure 15 Correlation between experimental and calculated flow stress by regression model at strain of 0.5

where E is the sample of experimental value, P is the sample of predicted value by ANN model and N is the number of strain–stress samples.

The comparison of η -values of the ANN model and the regression model is shown in Figure 16. It can be demonstrated that the η -values obtained from the ANN model vary from -2.54% to 2.34% , whereas for the regression model, the η -values are in the range from -17.75% to 18.33% . Subsequently, the distribution of η -values was analyzed further since the larger fluctuation range of η -values does not mean poorer predictability. Figure 17(a) and 17(b) shows the distribution of η -values corresponding to the well-trained ANN model and regression model, respectively, in which the height of each histogram expresses the relative frequency of each η -level. The

distribution diagrams of η -values appear to be typical Gaussian distributions after being nonlinearly fitted. The two indicators, namely mean value of η -values (μ) and standard deviation (w), are of great significance for evaluating the two Gaussian distributions. Mean value is a evaluator obtained by dividing the sum of observed values by the number of observations to measure the magnitude of the datasets, while standard deviation (w) represents the degree of dispersion and gives an idea of how close the entire set of data is to the average value, as expressed by eqs (12) and (13) [7, 23, 27]:

$$\mu = \frac{1}{N} \sum_{i=1}^N \eta_i \quad (12)$$

$$w = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (\eta_i - \mu)^2} \quad (13)$$

where η is the sample of relative percentage error, μ is the mean value of η -values and N is the sample number of relative percentage errors.

Small values of μ and w indicate tightly grouped, precise data. As shown in Figure 17(a) and 17(b), μ -value and w -value of the ANN model are -0.1264% and 0.8745% , respectively, compared with the 1.3146% and 8.2033% from the regression model. The smaller μ -value of the ANN model indicates that the predicted stress data are closer to the experimental stress data. And the smaller standard deviation (w) of the ANN model is related to a more centralized distribution of η -values, that is, it is of greater possibility for more samples in the predicted stress data to be close to the experimental stress data.

Figure 17 Distribution on relative percentage error by (a) ANN model and (b) regression model

Prediction potentiality of ANN model outside of experimental conditions

As stated above, the well-trained ANN model for as-forged Ti-10V-2Fe-3Al alloy is effective in flow stress prediction under limited experimental conditions and it has a great generalization capability. For the purpose of testing the prediction potentiality of the well-trained ANN model outside of experimental conditions, the flow stresses at supposed strain rates of 0.002 s^{-1} , 0.02 s^{-1} , 0.2 s^{-1} and 2 s^{-1} under temperature of 1,023 K, and the flow stresses at supposed temperatures of 958 K, 983 K, 1,008 K, 1,033 K, 1,058 K, 1,083 K and 1,108 K under strain rate of 0.1 s^{-1} were predicted for as-forged Ti-10V-2Fe-3Al alloy, as shown in Figure 18(a) and 18(b), respectively. In Figure 18, each solid line represents the 3D response plot of experimental stresses; meanwhile each dash line composed of a rhombus matrix represents the 3D response plot of predicted stresses outside of experimental conditions. It can be noticed that the predicted stress out of experimental conditions matches well with the shape of the experimental strain–stress curves, articulating similar intrinsic characteristics with experimental strain–stress curves, that is, the well-trained ANN model has great generalization ability and prediction potentiality to deal with the constitutive relationships of as-forged Ti-10V-2Fe-3Al alloy.

Conclusions

An ANN model has been developed to deal with the flow behaviors of as-forged Ti-10V-2Fe-3Al alloy using experimental data from hot compression tests in the temperature range of 948–1,123 K and strain rate range of $0.001\text{--}10 \text{ s}^{-1}$. The following conclusions can be drawn:

Figure 18 The 3D plot of flow stress at (a) temperature of 1,023 K under strain rates of 0.002 s^{-1} to 2 s^{-1} and (b) strain rate of 0.1 s^{-1} under temperatures of 958 K to 1,108 K

1. The average Q -value of as-forged Ti-10V-2Fe-3Al alloy in β -phase temperature range is almost equal to the self-diffusion activation energy of 166 kJ/mol for β -Ti, while the Q -value of as-forged Ti-10V-2Fe-3Al

alloy in $\alpha + \beta$ -phase temperature range is much larger than the self-diffusion activation energies of α -Ti (242 kJ/mol) and β -Ti (166 kJ/mol), which reveals that the softening mechanism in different phase temperature ranges is different in the hot deformation of as-forged Ti-10V-2Fe-3Al alloy, and the flow behaviors of as-forged Ti-10V-2Fe-3Al is extremely complex, especially those in a wide temperature range involving transformation.

- The value of R in training procedure was calculated to be 0.9999, and the R -values in testing procedure were calculated to be 0.99981 and 0.99984, corresponding to $\alpha + \beta$ -phase temperature range and β -phase temperature range, respectively. High level of R -values demonstrates a very good correlation relationship between experimental and predicted stress values by the ANN model, and the model was well trained with an excellent generalization capability.
- At strain of 0.5, R and AARE for the regression model are 0.9998 and 0.572%, respectively, compared with the 0.9902 and 6.583% for the ANN model. Higher R -values and lower AARE-values indicate a better predictability of the ANN model under limited experimental conditions than that of the regression model.
- At strain of 0.5, the mean value (μ) and standard deviation (w) of the well-trained ANN model are -0.1264% and 0.8745% , respectively, while their values of the improved Arrhenius-type model are 1.3146% and 8.2033% , respectively. Lower μ -value and w -value for the ANN model indicate that it has a good generalization capability for testing work.
- The predicted strain–stress curves outside of the experimental conditions from the well-trained ANN model accurately fit the complex nonlinear hot deformation behaviors, providing further evidence for the excellent generalization capability of the ANN model for as-forged Ti-10V-2Fe-3Al alloy.

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References

- Boyer RR, Kuhlman GW. Processing properties relationships of Ti-10V-2Fe-3Al. *Metall Mater Trans A* 1987;18:2095–103.
- Balasubrahmanyam V, Prasad Y. Hot deformation mechanisms in metastable beta titanium alloy Ti-10V-2Fe-3Al. *Mater Sci Technol* 2001;17:1222–8.
- Weiss I, Semiatin SL. Thermomechanical processing of beta titanium alloys—an overview. *Mater Sci Eng A* 1998;243:46–65.
- Serajzadeh S. Prediction of thermo-mechanical behavior during hot upsetting using neural networks. *Mater Sci Eng A* 2008;472:140–7.
- Samantaray D, Mandal S, Bhaduri AK, Venugopal S, Sivaprasad PV. Analysis and mathematical modelling of elevated temperature flow behaviour of austenitic stainless steels. *Mater Sci Eng A* 2011;528:1937–43.
- Zhu Y, Zeng W, Sun Y, Feng F, Zhou Y. Artificial neural network approach to predict the flow stress in the isothermal compression of as-cast TC21 titanium alloy. *Comput Mater Sci* 2011;50:1785–90.
- Han Y, Qiao G, Sun J, Zou D. A comparative study on constitutive relationship of as-cast 904L austenitic stainless steel during hot deformation based on Arrhenius-type and artificial neural network models. *Comput Mater Sci* 2013;67:93–103.
- Quan GZ, Lv WQ, Mao YP, Zhang YW, Zhou J. Prediction of flow stress in a wide temperature range involving phase transformation for as-cast Ti-6Al-2Zr-1Mo-1V alloy by artificial neural network. *Mater Des* 2013;50:51–61.
- Sheikh H, Serajzadeh S. Estimation of flow stress behavior of AA5083 using artificial neural networks with regard to dynamic strain ageing effect. *J Mater Process Technol* 2008;196:115–19.
- Malinov S, Sha W. Application of artificial neural networks for modelling correlations in titanium alloys. *Mater Sci Eng A* 2004;365:202–11.
- Guo Z, Malinov S, Sha W. Modelling beta transus temperature of titanium alloys using artificial neural network. *Comput Mater Sci* 2005;32:1–12.
- Quan GZ, Yu CT, Liu YY, Xia YF. A comparative study on improved Arrhenius-type and artificial neural network models to predict high-temperature flow behaviors in 20MnNiMo alloy. *Sci World J* 2014;2014:108492.
- Peng W, Zeng W, Wang Q, Yu H. Comparative study on constitutive relationship of as-cast Ti60 titanium alloy during hot deformation based on Arrhenius-type and artificial neural network models. *Mater Des* 2013;51:95–104.
- Quan GZ, Wang Y, Yu CT, Zhou J. Hot workability characteristics of as-cast titanium alloy Ti-6Al-2Zr-1Mo-1V: A study using processing map. *Mater Sci Eng A* 2013;564:46–56.
- Quan GZ, Wu DS, Luo GC, Xia YF, Zhou J, Liu Q, et al. Dynamic recrystallization kinetics in α phase of as-cast Ti-6Al-2Zr-1Mo-1V alloy during compression at different temperatures and strain rates. *Mater Sci Eng A* 2014;589:23–33.
- Huang YC, Lin YC, Deng J, Liu G, Chen MS. Hot tensile deformation behaviors and constitutive model of 42CrMo steel. *Mater Des* 2014;53:349–56.
- Yang Z, Guo YC, Li JP, He F, Xia F, Liang MX. Plastic deformation and dynamic recrystallization behaviors of Mg-5Gd-4Y-0.5Zn-0.5 Zr alloy. *Mater Sci Eng A* 2008;485:487–91.
- Lin YC, Chen XM. A critical review of experimental results and constitutive descriptions for metals and alloys in hot working. *Mater Des* 2011;32:1733–59.
- Serajzadeh S. Prediction of temperature distribution and required energy in hot forging process by coupling neural networks and finite element analysis. *Mater Lett* 2007;61:3296–300.
- Phaniraj MP, Lahiri AK. The applicability of neural network model to predict flow stress for carbon steels. *J Mater Process Technol* 2003;141:219–27.

21. Lucon PA, Donovan RP. An artificial neural network approach to multiphase continua constitutive modeling. *Compos Part B Eng* 2007;38:817–23.
22. Juang SC, Tarng YS, Lii HR. A comparison between the back-propagation and counter-propagation networks in the modeling of the TIG welding process. *J Mater Process Technol* 1998;75:54–62.
23. Chai RX, Guo C, Yu L. Two flowing stress models for hot deformation of XC45 steel at high temperature. *Mater Sci Eng A* 2012;534:101–10.
24. Lin YC, Wen DX, Deng J, Liu G, Chen J. Constitutive models for high-temperature flow behaviors of a Ni-based superalloy. *Mater Des* 2014;59:115–23.
25. Lin YC, Liu G, Chen MS, Zhong J. Prediction of static recrystallization in a multi-pass hot deformed low-alloy steel using artificial neural network. *J Mater Process Technol* 2009;209: 4611–16.
26. Lin YC, Chen XM, Wen DX, Chen MS. A physically-based constitutive model for a typical nickel-based superalloy. *Comput Mater Sci* 2014;83:282–9.
27. Mandal S, Sivaprasad PV, Venugopal S, Murthy KP. Artificial neural network modeling to evaluate and predict the deformation behavior of stainless steel type AISI 304L during hot torsion. *Appl Soft Comput* 2009;9:237–44.