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Artificial neural network and constitutive equations to predict the hot deformation behavior of modified 2.25Cr–1Mo steel

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ABSTRACT

Hot compression tests of modified 2.25Cr–1Mo steel were conducted on a Gleeble-3500 thermo-mechanical simulator at the temperatures ranging from 1173 to 1473 K with the strain rate of 0.01–10 s^{-1} and the height reduction of 60%. Based on the experimental results, an artificial neural network (ANN) model and constitutive equations were developed to predict the hot deformation behavior of modified 2.25Cr–1Mo steel. A comparative evaluation of the constitutive equations and the ANN model was carried out. It was found that the relative errors based on the ANN model varied from −4.63% to 2.23% and those were in the range from −20.48% to 12.11% by using the constitutive equations, and the average root mean square errors were 0.62 MPa and 7.66 MPa corresponding to the ANN model and constitutive equations, respectively. These results showed that the well-trained ANN model was more accurate and efficient in predicting the hot deformation behavior of modified 2.25Cr–1Mo steel than the constitutive equations.

1. Introduction

For the purpose of lowering down the power generators' cost, it is necessary to improve plant efficiency through raising of the steam pressure and temperature. The progressive increase of steam parameters leads to new requirements to steels used in the boiler and piping system [1,2]. Modified 2.25Cr–1Mo steel is a new advanced low alloy steel used for water walls of modern industrial boilers, which has excellent mechanical properties at elevated temperatures and improved weldability as a result of the enhanced alloying [3]. In comparison with conventional 2.25Cr–1Mo steel, modified 2.25Cr–1Mo steel has a small addition of V, Ti, Ni, N elements and its carbon content is reduced to below 0.10%.

A comprehensive study on hot deformation behavior of materials is quite important for the optimization of the thermo-mechanical process parameters as it directly affects the microstructure evolution of the materials and the mechanical properties of the formed product [4,5]. Hot deformation behavior of materials is always associated with various interconnecting metallurgical phenomena, such as work hardening, dynamic recovery, dynamic recrystallization and flow instabilities [6]. The constitutive relationship is the basic function of flow stress which describes the correlation of material properties with hot processing parameters such as strain, strain rate and deformation temperature [7]. In order to explore and understand the hot deformation behavior of materials, many researchers have made use of the regression method to develop constitutive equations over the past few years [8–11], which would give a complete mathematical description of the flow stress of materials. Mandal et al. [8] developed constitutive equations to predict the flow stress of a Ti-modified austenitic stainless steel. Cai et al. [9] developed the constitutive equations of different phase regimes to study the workability of Ti–6Al–4V alloy. However, the effects of many factors on the flow stress are complex and the relationship between the flow stress and the factors is nonlinear, which can reduce the accuracy of prediction by the regression method and limit the applicable range. Moreover, the development of such constitutive equations is always time consuming.

Fortunately, unlike the regression method, the artificial neural network method does not need to postulate a mathematical model or identify its parameters. The ANN can provide a fundamentally different approach to materials modeling and processing control techniques from statistical or numerical methods [12]. And the ANN learns from training data and recognizes patterns in a series of input and output values without any prior assumptions about their nature and interrelations [13]. Artificial neural network with the ability to learn from small experimental values is an intelligent

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information treatment system with the characteristics of understanding, memorizing and generalizing the rules of the material behavior. Therefore, the ANN model has better performances compared with the constitutive equations, and it has been successfully applied to predict the hot deformation behavior of some alloys in the recent years. Lin et al. [14] predicted the flow stress of 42CrMo steel in the hot compressive deformation tests by using ANN model and pointed out that the experimental and predicted results showed a good correlation. Mandal et al. [15] pointed out that the ANN model was an efficient tool to evaluate and predict the deformation behavior of stainless steel type AISI 304L. Sun et al. [16] developed the constitutive relationship model for Ti40 alloy and indicated the predicted flow stress by the ANN model was in good agreement with experimental results.

However, very limited efforts have been directed to understand and predict the flow behavior of modified 2.25Cr–1Mo steel. In our recent work [11], it was found that the predicted results of the hot deformation behavior of T24 ferritic steel at high temperature of 1323–1473 K by using Arrhenius-type equations model showed a good agreement with the experimental values. However, the Arrhenius-type equations were too complex, the constitutive relationship was nonlinear and further extended to prediction of the flow stress under the deformation temperatures that lower than 1323 K was not included in compression tests. In the present investigation, hot compression tests of modified 2.25Cr–1Mo steel were conducted at wide and practical deformation temperatures ranging from 1173 to 1473 K with the internal of 50 K, and constitutive relationship of modified 2.25Cr–1Mo steel was established by a three-layer feed forward artificial neural network model and constitutive equations respectively. The comparisons between the experimental and the predicted flow stress of modified 2.25Cr–1Mo steel by using the constitutive equations as well as the ANN model were carried out. Furthermore, the suitability of the constitutive equations and the trained ANN model was evaluated in terms of correlation coefficient, average absolute relative error, average root mean square error, normalized bias error and relative error.

2. Materials and experimental procedures

The chemical composition of modified 2.25Cr–1Mo steel used in the present investigation is given in Table 1. Cylindrical specimens with 10 mm in diameter and 15 mm in height were machined to perform compression tests. The flat ends of the specimen were recessed to a depth of 0.2 mm to entrap the lubricant of graphite to minimize the frictions between the specimens and anvils during the hot deformation tests. The isothermal hot compression tests were conducted on a Gleeble-3500 thermo-mechanical simulator at the deformation temperatures ranging from 1173 to 1473 K with the interval of 50 K and under four different strain rates (0.01, 0.1, 1 and 10 s^{-1}). The height reduction of the specimens was 60% by the end of the compression tests. Prior to compression tests, each specimen was heated to the deformation temperature at a rate of 10 K s^{-1} and held for 3 min to obtain a uniform deformation temperature. The true stress-true strain curves were recorded automatically in the isothermal compression process. The specimens were immediately quenched in water after deformation to retain the microstructures at elevated temperature.

3. Development of artificial neural network model

A typical artificial neural network consists of an input layer, an output layer and one or more hidden layers. The input layer is used to receive data from outside and the output layer sends the information out, while the hidden layer that contains a systematically determined the number of processing elements is to provide the necessary complexity for nonlinear problems. It is fairly important to determine the learning method for the ANN model. One of the most popular learning method is the back-propagation (BP) learning algorithm, which is a typical means of adjusting the weights and biases by utilizing gradient descent to minimize the target error in a particular training pattern [17,18]. Therefore, a three-layer feed forward back-propagation artificial neural network (as shown in Fig. 1) was employed to predict the flow behavior and model the constitutive relationship of modified 2.25Cr–1Mo steel in present work. The input parameters of the ANN model are the strain (ε), strain rate ($\dot{\varepsilon}$) and deformation temperature (T), and the output is the flow stress (σ).

Before training the artificial neural network model, both input and output variables should be normalized within the range from 0 to 1 in order to obtain a usable form for the network to read. The pre-processing procedure, which can make the neural network training more efficiency, was selected in the following equation:

$$X' = \frac{X - 0.95X_{\min}}{1.05X_{\max} - 0.95X_{\min}} \tag{1}$$

where X is the original data, X' is the unified data of the corresponding X, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of X, respectively. Eq.(1) was used to unify data T and σ in the present paper. Since the data of ε are already in the range of 0–1, they do not need further unification. However, as $\dot{\varepsilon}$ changed sharply and after unification the minimum value of $\dot{\varepsilon}$ was too small for the ANN to learn, the following equation is adopted to unify the values of $\dot{\varepsilon}$:

$$\dot{\varepsilon}' = \frac{(3 + \lg\dot{\varepsilon}) - 0.95(3 + \lg\dot{\varepsilon}_{\min})}{1.05(3 + \lg\dot{\varepsilon}_{\max}) - 0.95(3 + \lg\dot{\varepsilon}_{\min})} \tag{2}$$

in which a constant 3 is added in order to make the unified data be positive.

It is found that one hidden layer is adequate for the present work. However, the number of neurons in hidden layer determines the complexity of network and precision of predicted values. It is extremely complicated to choose the number of neurons in hidden layer. As a result, in order to decide the appropriate number of neurons, a trial-and-error procedure was started with two neurons in hidden layer and further carried out with more neurons. The convergence criterion for the ANN model was determined by the average root mean square error (RMSE) between the desired and predicted output values. Fig. 2 showed the influence of the number of neurons in hidden layer on the network performance. It was found that the network with one hidden layer consisting of 16 hidden neurons had a minimum average root mean square error and thereby considered as the optimal structure for the prediction of hot deformation behavior of modified 2.25Cr–1Mo steel.

Training is the process in which the network's predictions are refined to fit the experimental data, which is based on the availability of input data and the reliability of the output data. The transfer functions were 'tan sigmoid' and 'pure linear', and the

Table 1
The chemical composition (in wt.%) of modified 2.25Cr–1Mo steel.

C	Cr	Mo	Mn	V	Si	Cu	Ti	Ni	Al	N	Fe
0.067	2.408	1.033	0.469	0.236	0.207	0.092	0.062	0.038	0.1	0.008	Bal.