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Effect of hafnium on creep behavior of a corrosion resistant nickel base superalloy

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ABSTRACT

The effect of the selective additions of hafnium (Hf) on the variation of creep life and microstructure of an experimental nickel base superalloy has been investigated. Artificial neural networks (ANNs) were utilized to predict the effect of Hf content on the creep rupture life at temperatures of 850–950 °C and showed that, with the addition of Hf, the creep life was prolonged. This effect was more pronounced at low stress than at high stress and was most noticeable with the first 0–0.6 wt% of Hf addition. Analysis of the correlation between microstructure and creep life of 0.4 wt% Hf doped alloy revealed that at low stresses the initiation and propagation of microcracks from MC carbides was retarded, and the beneficial effect of grain boundary strengthening on creep life was significant, although the tendency of appearance of γ′ rafting in 0.4 wt% Hf doped alloy is very close to that in Hf-free alloy. This was in agreement with above ANNs prediction. In addition, the relationship between the appearance of γ′ rafting and lattice misfit with regards to Hf content was discussed.

1. Introduction

Corrosion resistant superalloys have been employed specifically for the production of industrial gas turbine blades for many years, but the life of this component is limited by the creep deformation and fracture. It is believed that the addition of minor elements such as carbon, boron, hafnium and zirconium in the alloys can improve the creep properties through grain boundary strengthening [1,2]. The role of Hf on the mechanical properties of superalloys is based on precipitation strengthening of the γ′ phase [3]. The amount limit of Hf addition is 0.5 wt% in an earlier study [4], however, it is found in later experiments that Hf is beneficial to creep properties in amount of ~1.5 wt% [1]. Actually, this depends on the alloy type and service condition. Hf is used mainly to improve the intermediate temperature creep properties or to reduce the tendency for grain boundary tearing during directional solidification. In addition, at high temperatures, Hf has a strong affinity for sulfur so that it can prevent grain boundary embrittlement caused by sulfur. Hf has also been seen to have a slight impact on yield strength and hold-time-crack growth rates [5].

In this study, the effect of Hf on creep rupture life, creep stability and element segregation is discussed in a corrosion resistant superalloy. A three-layer artificial neural network (ANN) was set up to predict creep rupture life, using the 16 chemical elements, grain size, heat-treatment temperature and hold time, test temperature and stress to make 25 input parameters into the algorithm. The Levenberg–Marquardt (LM) learning algorithm was employed to train the model by using laboratory experimental data. This trained network was tested on a single set separated from the rest of the data and a good correlation between the experimental and predicted results has been obtained. Finally, the ANN simulated results show the effect of Hf content on the creep rupture life at selective temperatures and stress. To study the microstructural characteristics in conjunction with the creep properties, the authors undertake a detailed analysis on carbides, grain boundary, and γ′ stability in Hf-free alloy and 0.4 Hf alloy. An attempt has been made to correlate microstructure and creep rupture life at the investigated temperatures and stresses.

2. Experimental

The alloys studied in the work are based on a corrosion experimental alloy with chemical composition in wt%: 15.5 Cr, 10.8 Co, 5.6 W, 2.1 Mo, 3.2 Al, 4.6 Ti, 0.2 Nb, 0.075 B, 0.075 C and the balance Ni (Hf-free alloy). This composition has been modified with the addition of 0.25 wt% Hf doped alloy (0.25 Hf alloy) and 0.4 wt% Hf doped alloy (0.4 Hf alloy). The alloys were produced in an industrial scale vacuum induction furnace. The ingots were given standard heat treatment as follows: 1170 °C, 4 h, A.C. +1050 °C, 4 h, A.C. +850 °C, 16 h, A.C. Creep rupture tests were performed at 800–950 °C over a stress range of 120–500 MPa in air. The creep specimens were of 10 mm diameter and 100 mm gauge length. The temperature along the gauge length was maintained at ±2 °C through out the creep test. Most of creep tests were

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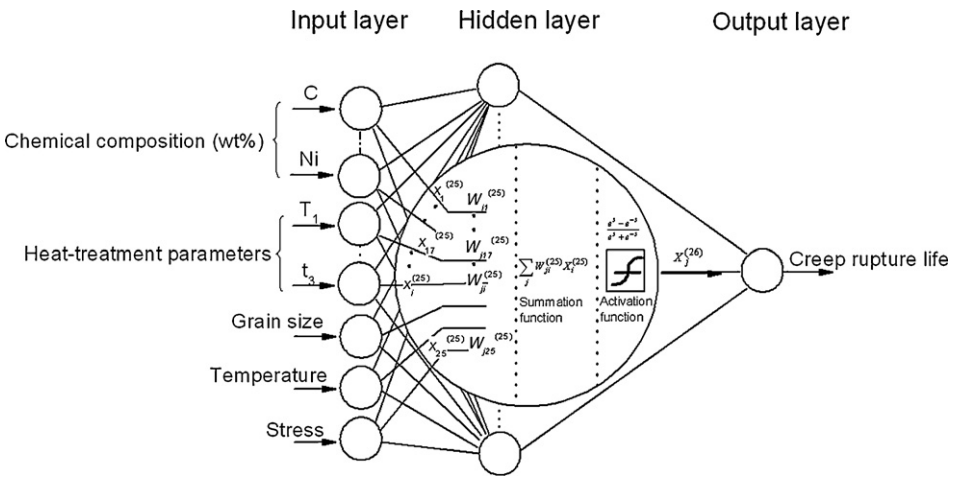

Fig. 1. A schematic description of artificial neural network configuration and the relationships between the input and output vectors of one neuron.

run to rupture, whereas some tests were interrupted for scanning electron microscopy (SEM) observations. The average element distribution was measured quantitatively with an electromicroprobe. The X-ray data were obtained from a Max-RA X-ray diffractometer with Cu Kα_1 radiation ($\lambda = 0.154056$ nm) in the angular range of $15^\circ \leq 2\theta \leq 85^\circ$ with a step size of $\Delta 2\theta = 0.02^\circ$. The time per step $t = 12$ s.

3. Artificial neural network model for creep rupture life

In the materials science field, the use of ANNs for forecasting, functional approximation, optimization, simulation, modeling and performance prediction of thermal systems has become increasingly popular in the last two decades due to its short development and fast processing speed [6–8]. ANNs can provide powerful empirical modeling techniques for complex experimental data, which may be nonlinear, inter-dependent, noisy and non-systematic. ANN architecture is composed by an input layer, an output layer and one or more hidden layers. The neuron (elementary processor of the ANN) is characterized by (i) the input being the sum of flow coming from the other neurons connected upstream; (ii) the activation function (transfer function) making the input nonlinear and animating the neuron by determining its activation; (iii) the output resulting from the transformation supplying the neurons connected downstream.

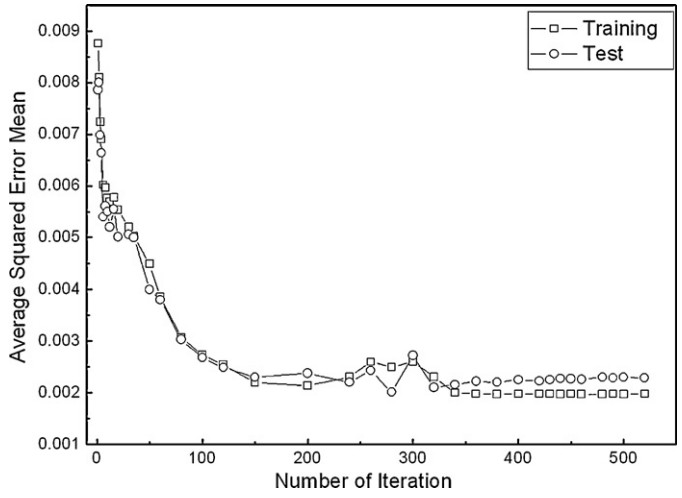

Fig. 2. Average squared error guessing mean with respect to number of iteration.

In this study, the feed-forward multilayer perception is used and trained with a back propagation algorithm. In conventionally cast superalloys, besides chemical composition, some other factors such as γ' precipitates and grain size can influence mechanical properties obviously. These microstructural characteristics, which should be included in NN input parameters, are hard to be specified. However, γ' characteristics of a given cast superalloy are directly dependent on heat treatment, and therefore heat-treatment parameters can be considered as indirect microstructural input parameters. Besides 16 chemical elements, grain size, temperature and stress, the following heat-treatment parameters are considered in input parameters: solution temperature (T_1) and holding time (t_1), high temperature aging (T_2) and holding time (t_2), and low temperature aging (T_3) and holding time (t_3) with the resulting creep life as the output of the neural network model. Thus, the structure of architecture is chosen as 25–*x*–1. Fig. 1 shows the structure of ANN model with various layers. The inputs and outputs should be first normalized within the range of 0–1 [7,9,10]. The output x_j produced by the neuron i in the hidden layer is given by the following relationship:

$$x_j = f\left(\sum_{i=1}^{n} W_{ji} X_i + b\right) \tag{1}$$

where f is the activation function, n the number of elements in the input layer, W_{ji} the weight associated with the connection between the neuron i in the input layer and the neuron j in the hidden layer, whose output is x_j, and b is the offset or bias which shifts the activation function along the basic axis. To evaluate the performance of such a network, the average squared output error (ASE) is used:

$$\mathrm{ASE} = \frac{1}{n}\sum_{j=1}^{n}[y(j) - d(j)]^2 \tag{2}$$

where $y(j)$ is output of real data, $d(j)$ is the network desired or target output value for the jth sample and n is the total number of data points.

4. Results and discussions

4.1. Modeling results

Data used in this work was got from the China Aeronautical Materials Handbook [11] and materials database [12]. Fig. 2 shows the relation between absolute error and interaction. To balance the accuracy and convergence speed, 400 iterations were performed