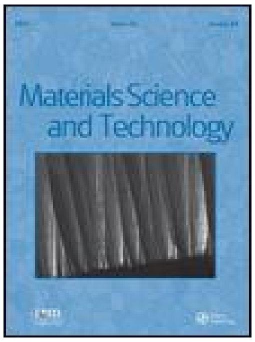

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Artificial neural network modelling to predict hot deformation behaviour of as HIPed FGH4169 superalloy

C. G. Yao[1,2], B. Wang[1], D. Q. Yi*[1], B. Wang*[1] and X. F. Ding[1]

The hot deformation behaviour of as HIPed FGH4169 superalloy was studied by single stroke compression test on MMS-200 test machine at the temperatures of 950–1050°C and the strain rates of 0·004–10 s^{-1}. Based on the experimental results, a back-propagation artificial neural network model and constitutive equation method were established to predict the flow stress of FGH4169 superalloy. The predictability of two different models was compared. The correlation coefficients of experimental and predicted flow stress with the trained BP ANN model and constitutive equation were 0·9995 and 0·9808 respectively. The average root mean square error (RMSE) values of the trained ANN model and constitutive equation are 0·39 and 2·21 MPa respectively. And the average absolute relative error (AARE) values of the trained ANN model and constitutive equation are 1·79 and 7·47% respectively. The results showed that the ANN model is an effective tool to predict the flow stress in comparison with constitutive equation.

Keywords: FGH4169 superalloy, Hot deformation behaviour, Artificial neural network, Constitutive equation

Introduction

GH4169 (Inconel 718) superalloy is one of the most widely used nickel base superalloys, which has been widely used in gas turbine and related aircraft/aerospace applications due to its good mechanical properties and structure stability at elevated temperature.[1,2] The hot deformation behaviour of alloys is strongly dependent on the processing parameters, i.e. temperature, strain rate and strain.[3,4] Therefore, the understanding of the behaviour related to the mentioned parameters is necessary.

Hot deformation behaviour is always associated with metallurgical phenomena such as work hardening, dynamic recovery (DRV), dynamic recrystallisation (DRX) and flow instability. Work hardening increases the flow stress of materials while phenomena like DRV or DRX cause dynamic softening. These metallurgical phenomena result in highly non-linear deformation behaviour. Therefore, it is quite complex in nature, but at the same time, is significant to predict the non-linear relationships between flow stresses and deformation parameters.

The constitutive equation is the basic function of flow stress which describes the correlation of material properties with hot processing parameters.[5] In order to explore and describe the hot deformation behaviour of materials, constitutive equations were established with regression method over the past decades,[3,6–8] which would give a complete mathematical description of the flow stress of materials. Wang[3] developed the constitutive equation of Inconel 718 alloy to understand the flow behaviour. Yuan[8] established the constitutive equation to describe the relationship among the peak stress, deformation temperature and strain rate of Inconel 718 alloy. However, the non-linear relationship between the flow stress and other parameters reduces the accuracy of prediction with the regression method.

Recently, artificial neural network (ANN) has been successfully applied for a variety of uses in the field of materials engineering. It provides an efficient alternative for understanding hot deformation behaviour. As a black box model, the neural networks are capable of solving highly complex problems without mathematical model. An ANN model can learn from the complex relationship of flow stress, strain, strain rate and temperature to predict the flow stress. A number of investigations on hot deformation behaviour with ANN models have been carried out on nickel alloy[9–10] and many other alloys.[4–5,11] Bariani[9] reported an application of ANN model in representing material response to hot forging cycles. Ravi[11] described how ANN model was used to capture the features of the processing map.

Accordingly, in the present study, FGH4169 was processed through powder metallurgy (P/M) hot isostatic pressing (HIP) route. Series hot compressions were conducted at different temperatures and strain rates. Flow stress shows non-linear relationship with processing parameters due to work hardening and dynamic recrystallisation. Investigations have been carried out to

[1]School of Materials Science and Engineering, Central South University, Changsha 410083, China
[2]Aerospace Research Institute of Materials & Processing Technology, Beijing 100076, China

*Corresponding authors, email yioffice@csu.edu.cn; wangbin325@263.net

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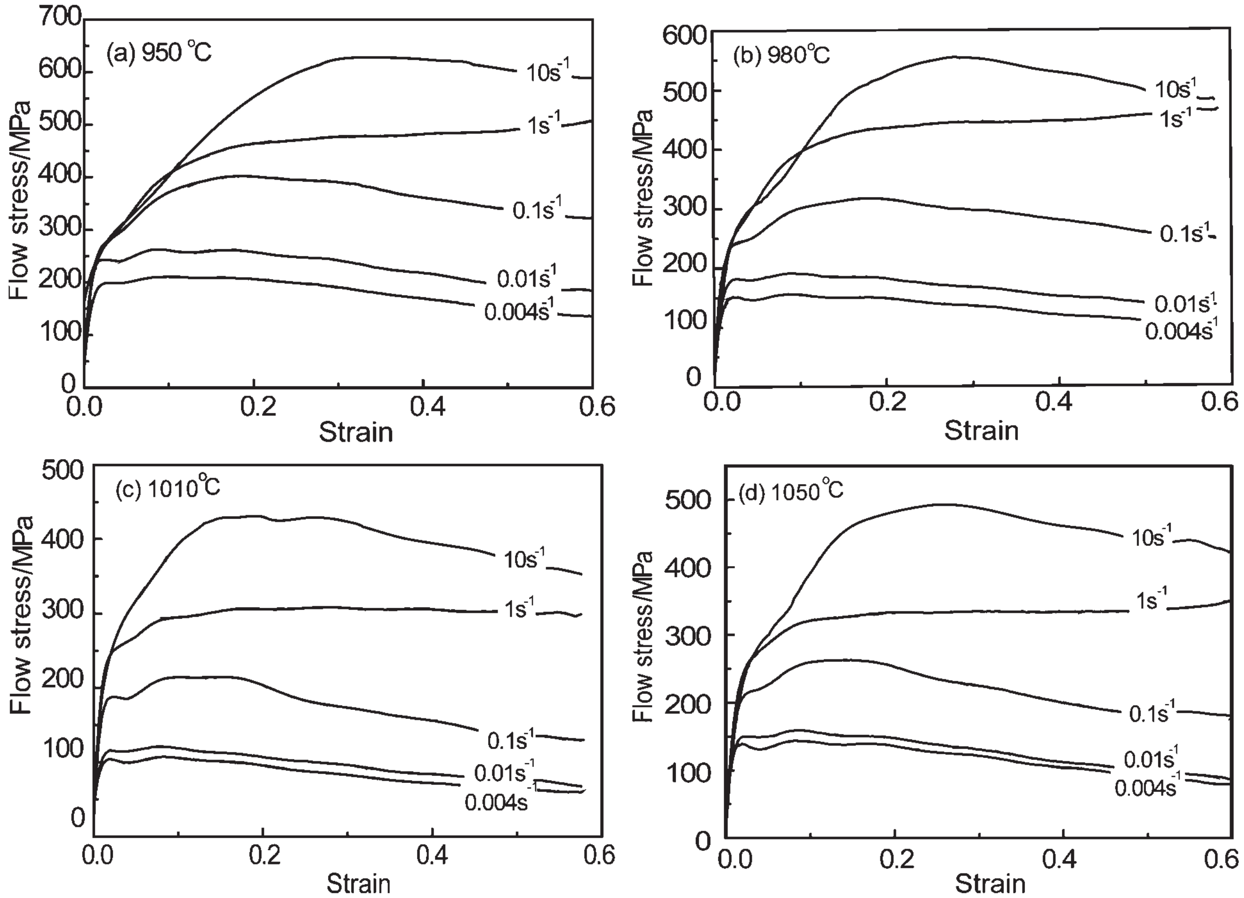


1 True stress–true strain curves of FGH4169 superalloy at various strain rates with temperatures of *a* 950°C, *b* 980°C, *c* 1010°C and *d* 1050°C

establish a constitutive model to predict the flow stress of FGH4169 superalloy with back-propagation neural network. Furthermore, constitutive equation was established to make a comparison with the trained ANN model in the aspect of flow stress prediction.

Experimental

The nominal chemical composition of as HIPed FGH4169 superalloy used in this work is: Ni–19·0Fe–18·3Cr–5·5Nb–3·05Mo–1·3Ti–0·59Al–0·029Mn. The delta aged FGH4169 superalloy was gained through a treatment: solution at 1100°C for 30 min, water quenching, followed by 900°C aging for 10 h. The cylindrical compression specimens of 8 mm in diameter and 12 mm in height were machined from the HIPed and delta aged superalloys respectively. Series of isothermal compression tests were conducted on MMS-200 thermo-simulation machine for the HIPed FGH4169 superalloy at deformation temperatures of 950, 980, 1010 and 1050°C. The strain rates were 0·004, 0·01, 0·1, 1·0 and 10 s^{-1} respectively. The same compression tests were conducted for the delta aged superalloy under the temperatures of 950 and 1050°C, and the strain rates of 0·004, 0·01, 0·1, 1·0 and 10 s^{-1}. The strain–stress curves were automatically recorded during the compression process. Upon compression, the specimens were cooled down to room temperature by water spraying.

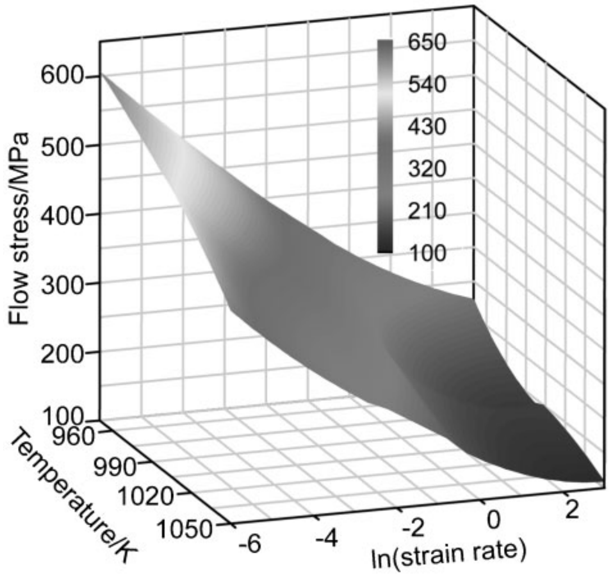
Flow behaviour of FGH4169 superalloy

The true stress–true strain curves obtained by hot compression under different temperatures are shown in Fig. 1. It can be seen clearly that almost all the curves exhibit the typical shape. The flow stress increases significantly with the increasing strain at the initial stage due to work hardening, and then the flow stress remains the same or starts to decrease because of dynamic recrystallisation.

Effect of temperature and strain rate on the flow stress at the strain of 0·5 is shown in Fig. 2. The flow stress is found to be sensitive to the variation of temperature and strain rate. The flow stress of FGH4169 superalloy generally decreases with increasing temperature at a constant strain rate. For instance, when deformation temperature increases from 950 to 1050°C, the peak stress decreases from 630 to 480 MPa at a strain rate of 10 s^{-1}. In addition, flow stress also increases with the increasing strain rate at a constant temperature.

Modelling with ANN

Artificial neural network (ANN) is a quite efficient learning tool for the generalisation of deformation behaviour characteristics. Generally, the typical structure of an ANN consists of an input layer, an output layer, and one or more hidden layers. The training of feed-forward neural networks is mainly undertaken using the back-propagation (BP) learning algorithm. Therefore, a three-layer feed-forward back-propagation ANN was applied to establish the constitutive relationship and predict the flow behaviour of FGH4169 superalloy. In the present work, the inputs of the ANN model contain the strain, strain rate and



2 Effect of temperatures and strain rates on flow stress at strain of 0·5

temperature, and the output contains the flow stress as shown in Fig. 3.

To establish the ANN model, both input and output variables should be normalised within the range from 0 to 1 before training the network. There is no need to normalise the variables of strain, since the values of them are already in the range from 0 to 1. The following equation (1) can be used to normalise the variables of flow stress and temperature[12]

$$X' = \frac{X - 0{\cdot}95X_{min}}{1{\cdot}05X_{max} - 0{\cdot}95X_{min}} \quad (1)$$

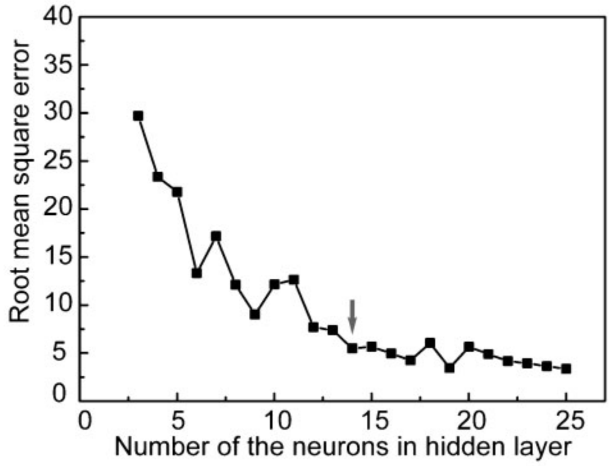
where X is the original data, X' is the normalised data of X, and X_{min} and X_{max} are the minimum and maximum values of X respectively.

However, the values of strain rate are discontinuous and change sharply. In addition, the normalised minimum value of strain rate is too small to use for ANN model learning. Therefore, the parameters of equation (1) are modified for strain rate as following[12]

$$\dot{\varepsilon}' = \frac{(3 + \lg\dot{\varepsilon}) - 0{\cdot}95(3 + \lg\dot{\varepsilon}_{min})}{1{\cdot}05(3 + \lg\dot{\varepsilon}_{max}) - 0{\cdot}95(3 + \lg\dot{\varepsilon}_{min})} \quad (2)$$

In which a constant 3 is added to the equation to make the data positive.

The neuron number for hidden layer was decided by a trial-and-error procedure in order to gain the optimum



4 Performance of BP ANN trained with different numbers of neurons, red arrow indicating optimum number

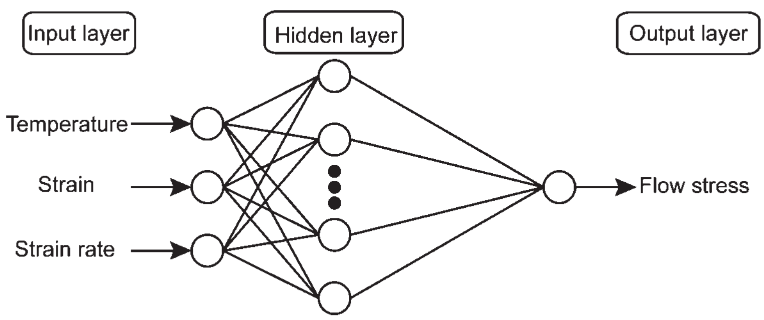
accuracy. It was tested with two neurons at first, and then carried out with more neurons until the performance of convergence criterion has reached an acceptable value. If the neuron number of each hidden layer in the ANN model is too small, the trained network may not learn the process sufficiently. However, too many neurons may slow the convergence rate or over fit the data.[4]

The convergence criterion for the ANN model was determined by the average root mean square error (RMSE) between the experimental and the predicted output values. RMSE is expressed as

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(E_i - P_i)^2\right]^{1/2} \quad (3)$$

where E and P are the experimental and predicted values of flow stress respectively; N is the total number of data used in the ANN model.

As is shown in Fig. 4, the average root mean square error (RMSE) decreases sharply with increasing number of neurons in the initial stage, and then tends to be steady. With the number of hidden neurons increasing, RMSE tends to gain a low value, which means high accuracy. However, the accuracy of the predicted flow stress is not satisfactory with more hidden layers. With more layers employed, the ANN model will gain the lower efficiency and need more calculation.[13] Therefore, a network with 14 hidden neurons produces best performance when BP algorithm is employed. In the same way, because of unavoidable noise in the sample data, the larger the number of training cycles is, the



3 Architecture of BP ANN model in present work

Table 1 Architecture and training parameters used in BP artificial neural network

BP ANN parameters	Selected values
Number of layers	3
Number of neuron on the layers	3–14–1
Initial weights and biases	Randomly between −1 and +1
Training parameters learning rule	Back-propagation
Initial learning rate	0·1
Momentum constant	0·9
Number of epochs	2000
Activation functions between Input and hidden layer	Tan-sigmoid
Activation functions between hidden and output layer	Pure linear
Training function	Trainlm

more the noise in the network will be recorded. The final network configuration is composed of parameters shown in Table 1.

In the present ANN model, 760 sets of data are selected from the true stress–true strain curves. During establishing the ANN model, 600 sets of data are used as training data, and the rest are used as the test ones.

Modelling with constitutive equation

The dependence of stress on the strain rate and temperature during hot deformation can be represented by constitutive equations proposed by Sellars and Tegart.[14] Combined with the Zener–Hollomon parameter Z,[15] the following equations can be used to describe the relationship

$$Z=\dot{\varepsilon}\exp\left(\frac{Q}{RT}\right) \tag{4}$$

$$\dot{\varepsilon}=A_1\sigma^{n1}\exp\left(-\frac{Q}{RT}\right) \tag{5}$$

$$\dot{\varepsilon}=A_2\exp\left(-\frac{Q}{RT}\right)\exp(\beta\sigma) \tag{6}$$

$$\dot{\varepsilon}=A[\sinh(\alpha\sigma)]^{n}\exp\left(-\frac{Q}{RT}\right) \tag{7}$$

where $\dot{\varepsilon}$ is the strain rate (s^{-1}), Q is the activation energy of hot deformation (J mol^{-1}), R is the universal gas constant (8·3145 J mol^{-1} K^{-1}), T is the absolute temperature (K), and σ is the flow stress (MPa). A_1, A_2, A, n, n_1, α and β are the material constants. After some of the constants are evaluated, the flow stress at a determined strain can be calculated by equation (8) with a Zener–Hollomon parameter[16]

$$\sigma=\frac{1}{\alpha}\ln\left\{\left(\frac{Z}{A}\right)^{1/n}+\left[\left(\frac{Z}{A}\right)^{2/n}+1\right]^{1/2}\right\} \tag{8}$$

In the present work, the deformation temperatures are 950, 980, 1010 and 1050°C and the experimental strain rates are 10, 1, 0·1, 0·01 and 0·004 s^{-1}. According to the true strain between 0·1 and 0·45 with interval of 0·05, selected flow stress is adopted to construct the constitutive

Table 2 Constant values of constitutive equation under different strains

	Constant values			
Strain	A/s^{-1}	α/MPa^{-1}	n	Q/kJ mol^{-1}
0·1	$1·173\times10^{17}$	$3·949\times10^{-3}$	5·584	448·754
0·15	$1·588\times10^{16}$	$3·703\times10^{-3}$	4·820	423·780
0·2	$5·079\times10^{17}$	$3·610\times10^{-3}$	4·559	459·660
0·25	$6·930\times10^{17}$	$3·599\times10^{-3}$	4·239	461·194
0·3	$1·157\times10^{18}$	$3·656\times10^{-3}$	4·038	466·355
0·35	$1·085\times10^{18}$	$3·810\times10^{-3}$	3·828	465·783
0·4	$4·666\times10^{17}$	$3·944\times10^{-3}$	3·671	457·014
0·45	$2·103\times10^{15}$	$4·068\times10^{-3}$	3·122	399·615

equation in the condition of different temperatures and strain rates. The main parameters can be calculated by the regression method, which are listed in Table 2.

The parameters (such as A, Q, n, α) in constitutive equation can be expressed by series polynomial fitting of variable strain, expressed as equation (9).[17] The polynomial fitting results of equation (9) are calculated and shown in Table 3

$$\begin{cases}\ln A=B_1\varepsilon^4+B_2\varepsilon^4+B_3\varepsilon^2+B_4\varepsilon^1+B_5\\ \alpha=C_1\varepsilon^4+C_2\varepsilon^4+C_3\varepsilon^2+C_4\varepsilon^1+C_5\\ n=D_1\varepsilon^4+D_2\varepsilon^4+D_3\varepsilon^2+D_4\varepsilon^1+D_5\\ Q=E_1\varepsilon^4+E_2\varepsilon^4+E_3\varepsilon^2+E_4\varepsilon^1+E_5\end{cases} \tag{9}$$

Comparison between ANN model and constitutive equation on hot deformation behaviour

The predictability of the trained BP ANN model and the constitutive equation is evaluated by standard statistical parameters. Besides the mentioned RMSE, shown in equation (3), there are correlation coefficient R, average absolute relative error $AARE$ and relative error RE, expressed as

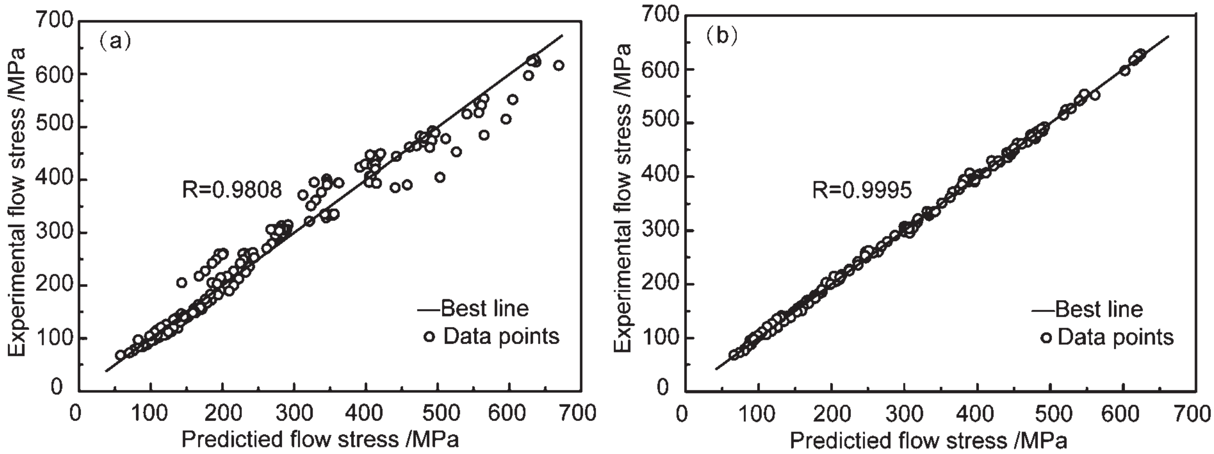
$$\mathrm{R}=\frac{\sum_{i=1}^{N}\left(E_i-\overline{E}\right)\left(P_i-\overline{P}\right)}{\left[\sum_{i=1}^{N}\left(E_i-\overline{E}\right)^2\sum_{i=1}^{N}\left(P_i-\overline{P}\right)^2\right]^{1/2}} \tag{10}$$

$$\mathrm{AARE}=\frac{1}{N}\left|\frac{E_i-P_i}{E_i}\right|\times100\% \tag{11}$$

$$RE=\left(\frac{E_i-P_i}{E_i}\right)\times100\% \tag{12}$$

Table 3 Coefficients of polynomial for ln$A$, α, n, (Q/100)

	Coefficients of			
i	ln$A$/B_i	α/C_i	n/D_i	(Q/100)/E_i
1	820·061	−0·0389	−16·277	90·717
2	−1950·605	0·00358	−98·558	−214·634
3	1067·685	0·0284	96·091	118·851
4	−190·668	−0·0117	−32·483	−21·931
5	49·235	0·00483	7·949	5·662



5 Relevance between experimental and predicted flow stress obtained by method of *a* constitutive equation and *b* ANN model

where E_i, P_i, N have been defined above; $\overline{E}$ and $\overline{P}$ are the average values of E and P respectively. The correlation coefficient R is a commonly used statistic and evaluated the linear relationship between the experimental and the calculated values. Relative error RE is used to compare the calculated values with the experimental one. ARRE is the unbiased statistics for evaluating the predictability of a model or equation.

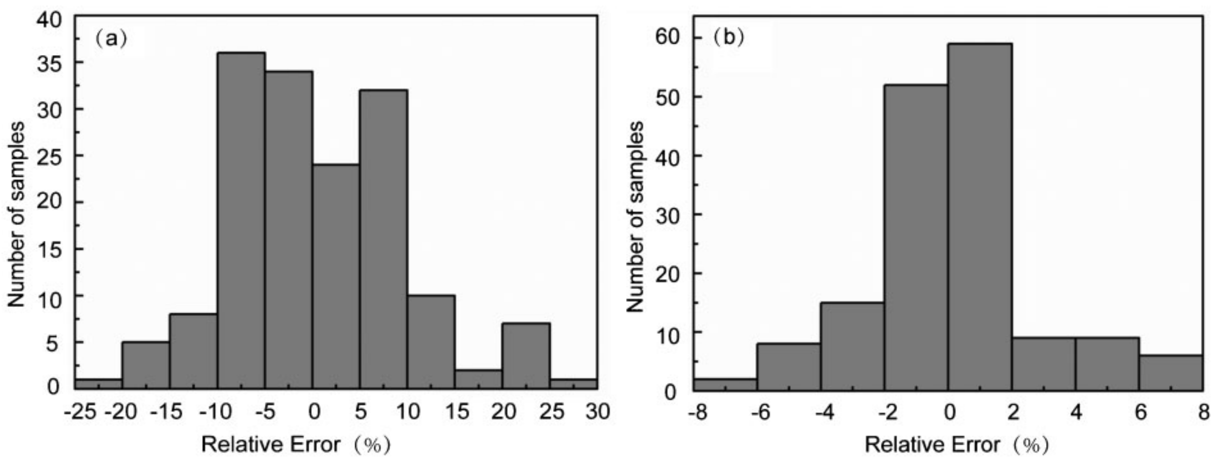
Figure 5 shows the relevance between experimental and predicted flow stress of FHG4169 superalloy gained by constitutive equation, as well as by ANN model. Almost all of the data points are close to the best line, and the R of the ANN model is 0·9995, which is higher than that of constitutive equation, 0·9808. Therefore, the ANN model has the better performance in comparison with constitutive equation in the aspect of predicting the flow stress of FGH4169 superalloy.

It is seen clearly that the values of both AARE and RMSE of ANN model are lower in comparison with those of constitutive equation. The RMSE values of the trained ANN model and constitutive equation are 0·39 and 2·21 MPa respectively. The *AARE* values of the trained ANN model and constitutive equation are 1·79 and 7·47% respectively. The predicted flow stress is closer to the experimental one of ANN model. Therefore, the accuracy of the ANN model is much higher than constitutive equation in the aspect of flow stress prediction.

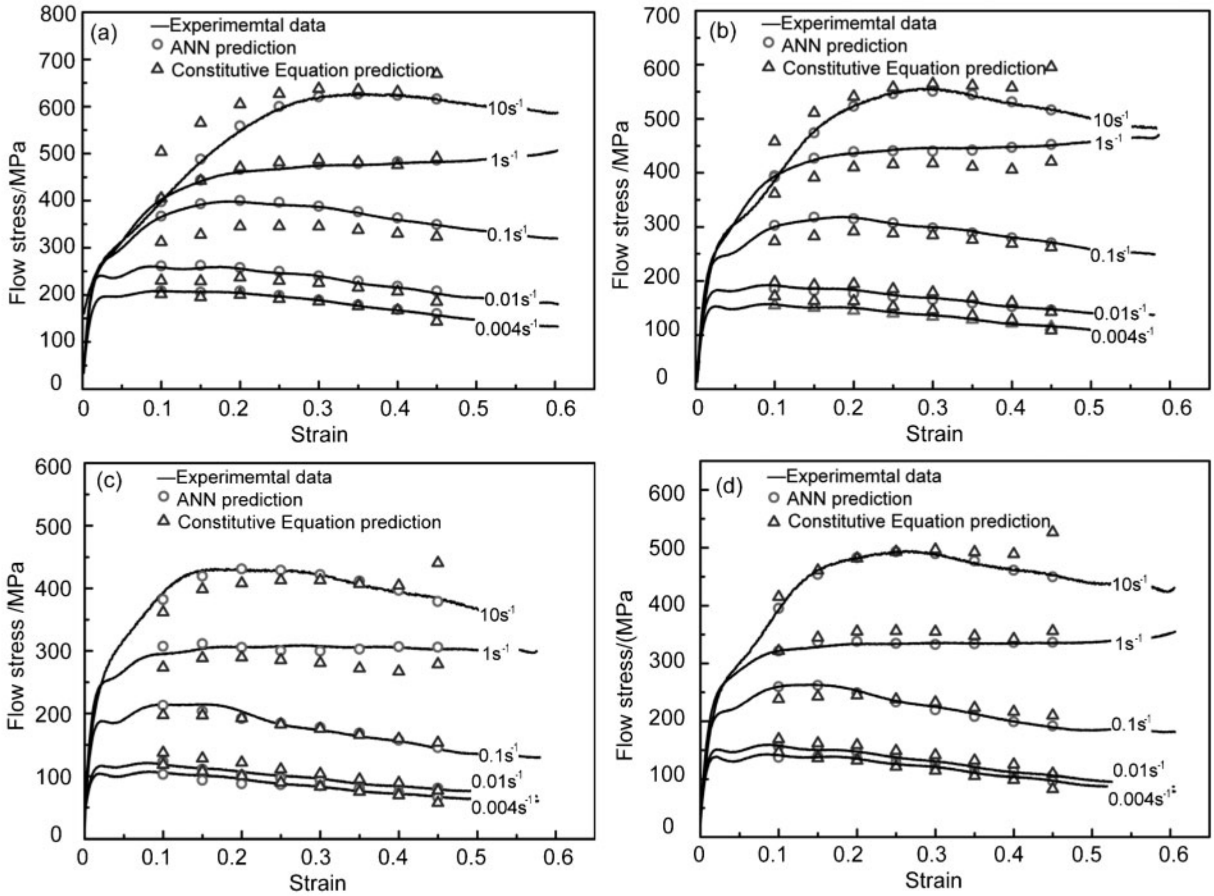
Furthermore, the relative error RE is also an efficient way to evaluate the performance of constitutive equation and the trained ANN model. The distribution of relative errors of two models has been graphically summarized in histograms as shown in Fig. 6. It is seen clearly that relative errors of the ANN model are mainly concentrated in the range from -2 to $+2\%$, while those of constitutive equation are concentrated in a wider range from -10 to $+10\%$. Therefore, the flow stress of FGH4169 superalloy predicted by ANN model is much more reliable than that predicted by constitutive equation.

According the comparison results of the values of statistical parameters for two models, it can be clearly found that the trained ANN model is more effective than the constitutive equation to predict the flow stress of FGH4169 superalloy.

The comparisons between experimental and predicted flow stress of FGH4169 superalloy with two different models are shown in Fig. 7. It can be observed directly that the flow stress predicted by the ANN model is consistent with the experimental one throughout the entire temperature and strain rate, revealing the metallurgical phenomena of the work hardening and dynamic softening. However, the predicted results of constitutive equation cannot fit the whole data well. There is a deviation between experimental and predicted flow stress by constitutive equation under some



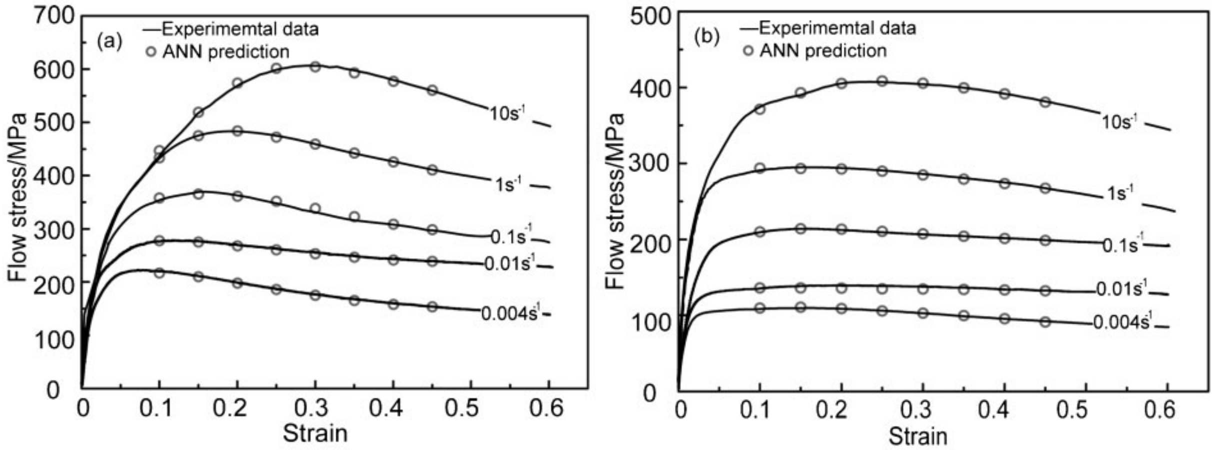
6 Histogram of relative errors for constitutive equation and trained ANN model respectively



7 Comparison of experimental and predicted flow stress of FGH4169 superalloy with two different models at various strain rates with temperatures of *a* 950°C, *b* 980°C, *c* 1010°C and *d* 1050°C

deformation condition, for example, at 950°C, $0{\cdot}1\ s^{-1}$. Therefore, the ANN model is more suitable to describe the flow stress of FGH4169 superalloy in comparison with constitutive equation.

For constitutive equation, the material constants should be calculated from original flow stress data previously, which takes a long time. However, there is no need for artificial neural network to do additional calculations. Furthermore, the ANN model is valid with specific input data for the alloy under different treatments as well as other alloys.[11] The flow stress of delta-aged FGH4169 superalloy is predicted with the previous ANN model. The parameters of the ANN model are the same as given in Table 1, while the input data has been adjusted according to the delta aged FGH4169 superalloy. The results of comparison between experimental and predicted flow stress of delta-aging FGH4169 superalloy with the ANN model are shown in Fig. 8. It can be observed directly that the predicted results are consistent with the experimental one. Therefore, the same ANN model can be used for other alloy to predict the flow stress. However, in the case of complex alloys with solid phase transformation (e.g. Ti alloys) under hot



8 Comparison of experimental and predicted flow stress of FGH4169 superalloy with trained ANN model at various strain rates with temperatures of *a* 950°C and *b* 1050°C

deformation, the model established above may have a limitation.

Conclusions

Hot deformation behaviour of FGH4169 superalloy at different temperatures (950, 980, 1010 and 1050°C) and different strain rates (0·004, 0·01, 0·1, 1·0 and 10 s^{-1}) was investigated. The flow stress increased significantly with the increasing strain at the initial stage due to work hardening, and then the stress remained the same or started to decrease because of dynamic recrystallisation. Based on the experimental results, a back-propagation artificial neural network model and constitutive equation model were established to predict the flow stress of FGH4169 superalloy. The predictability of two different models was compared. The correlation coefficients of the trained BP ANN model and constitutive equation were 0·9995 and 0·9808 respectively. The average root mean square error (RMSE) values of the trained ANN model and constitutive equation are 0·39 and 2·21 MPa respectively. And the average absolute relative error *AARE* values of the trained ANN model and constitutive equation are 1·79 and 7·47% respectively. Flow stress curves predicted by trained ANN model showed an accurate prediction of flow stress of FGH4169 superalloy, while that of constitutive equation was a rough prediction. Therefore, the ANN model is an effective tool to predict the flow stress in comparison with constitutive equation.

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Reference

1. R. B. Li, M. Yao, W. C. Liu and X. C. He: *Scr. Metall.*, 2002, **46**, 635–638.
2. S. C. Medeiros, Y .V. R. K. Prasad and W. G. Frazier: *Mater. Sci. Eng. A*, 2000, **A293**, 184–194.
3. Y. Wang, W. Z. Shao, L. Zhen, L. Yang and X. M. Zhang: *Mater. Sci. Eng. A*, 2008, **A497**, 479–486.
4. G. Z. Quan, W. Q. Lv, Y. P. Mao, Y. W. Zhang and J. Zhou: *Mater. Des.*, 2013, **50**, 51–61.
5. S. Mandal, P. V. Sivaprasad, S. Venugopal and K. P. N. Murthy: *Appl. Soft Comput.*, 2009, **9**, 237–244.
6. Y. Ning, M. W. Fu and X. Chen: *Mater. Sci. Eng. A*, 2012, **A540**, 164–173.
7. D. Y. Cai, L. Y. Xiong, W. C. Liu, G. D. Sun and M. Yao: *Mater. Des.*, 2009, **30**, 921–925.
8. H. Yuan and W. C. Liu: *Mater. Sci. Eng. A*, 2005, **A408**, 281.
9. P. F. Bariani, S. Bruschi and T. D. Negro: *J. Mater. Process. Technol.*, 2004, **152**, 395–400.
10. Y. Huang and P. L. Blackwell: *Mater. Sci. Technol.*, 2002, **18**, 1104–1108.
11. R. Ravi, Y. V. R. K. Prasad and V. V. Sarma: Proc. International Workshop on 'Neural network and genetic algorithm in material science and engineering', Howrah, India, January 2006, BESU, 257–271.
12. J. Liu, H. Chang, T. Y. Hsu and X. J. Ruan: *J. Mater. Process. Technol.*, 2000, **103**, 200–205.
13. R. H. Wu, J. T. Liu, H. B. Chang, T. Y. Hsu and X. Y. Ruan: *J. Mater. Process. Technol.*, 2001, **116**, 211–218.
14. C. M. Sellars and W. J. Tegart: *Membr. Sci. Rev. Met.*, 1966, **63**, 731.
15. C. Zener and J. H. Hollomon: *J. Appl. Phys.*, 1944, **15**, 22–32.
16. T. Sheppard and D. S. Wright: *Met. Technol.*, 1979, **6**, 215–223.
17. Y. C. Lin, M. S. Chen and J. Zhang: *Mater. Sci. Eng. A*, 2009, **A499**, 88–92.