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Prediction of flow stresses at high temperatures with artificial neural networks①

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[Abstract] On the basis of the data obtained on Gleeble-1500 Thermal Simulator, the predicting models for the relation between stable flow stress during high temperature plastic deformation and deformation strain, strain rate and temperature for 1420 Al-Li alloy have been developed with BP artificial neural networks method. The results show that the model on basis of BPNN is practical and it reflects the actual feature of the deforming process. It states that the difference between the actual value and the output of the model is in order of 5%.

[Key words] Al-Li alloy; high temperature plastic deformation; flow stress; neural networks
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1 INTRODUCTION

Generally alloy materials will present stable flow feature at high temperature plastic deformation, namely, under certain temperatures and strain rates true stresses (σ) will not apparently change with the continuous increasing of strains (ε) after true strains are beyond some values. The stable flow stresses models of alloy materials plastic deformation at high temperature are often developed by statistic method using gained experimental data. But since there are a lot of factors which have effects on flow stresses, the mathematical models which are developed by above methods are sometimes far away from complicated true deformations. The precision of models is restricted by deformation conditions, and the process of modelling is very troublesome and the working quantity is great. And that system modelling based on neural networks can make up this essential shortage[1~5]. Because the latter needn't make any hypothesis on studying objects when modeling, the model can approach true deformation process with its good mapping capacity[6~8]. Here by using the true measuring data gained at the compression test of 1420 alloy under high temperatures, a model of stable flow stresses for Al-Li alloys under high temperature plastic deformation has been developed according to the theory of BP algorithm.

2 EXPERIMENTAL

The experimental material was 1420 Al-Li alloy whose chemical compositions are given in Table 1.

This alloy was smelted and founded by IM. It

Table 1 Chemical compositions of 1420 Al-Li alloy (mass fraction, %)

Cu	Mg	Si	Li	Fe
0.05	5.44	0.013	2.15	0.02
Zr	Na	Ti	H/10^{-6}	Al
0.12	0.0004	0.05	0.6	Bal.

was melted and fined under the protection of flux, and being cast to circle ingots with diameter of 405 mm and length of 1 200 mm, and with water-cooling moulds under argon atmosphere. After the ingots being homogenized for 12 h at 455 ℃, from them small columnar samples with diameter of 8 mm and length of 12 mm were machined whose ends were machined to have simple grooves in order to deposit lubricant (75% lead and 25% machine oil, mass fraction) in order to reduce the friction between sample and press. The compression tests of equivalent temperatures and constant strain rates were performed on Gleeble-1500 Thermal Simulator and the samples were water quenched at once after deforming. Computer fully controlled the deformation process and automatically gathered the related data, and at the same time protracting the true stress-true strain curves of the experimental materials. The test temperatures used for 1420 Al-Li alloy test were 300, 350, 400, 450 and 500 ℃ and the strain rates used were 0.001, 0.01, 0.1, 1.0, 10.0 and 30.0 s^{-1} for each temperature, and the deformation strains were from 0 to 0.7 for each test.

The experimental scheme of compression tests for 1420 Al-Li alloy under equivalent temperatures and constant strain rates is listed in Table 2, where

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Table 2 Experimental deformation conditions

t/ ℃	$\dot{\varepsilon}$/ s^{-1}					
	0.001	0.01	0.1	1.0	10.0	30.0
300	C	T	C	T	C	T
350	T	C	T	C	T	C
400	C	T	C	T	C	T
450	T	C	T	C	T	C
500	C	T	C	T	C	T

T denotes that the data which are gained under some deformations are used for train sets, while C denotes check sets.

3 FUNDAMENTALS

3.1 BP algorithm of neural networks

In case the networks frame of BP algorithm has three layers. There are n input variables in input layer, l hidden layers and m output variables in output layer. The nodes for input layer, hidden layers and output layer are expressed by subscripts i, h, j separately, while the weight from node i of input layer to node h of hidden layer is expressed by w_{ih} and the weight from node h of hidden layer to node j of output layer is expressed by w_{hj}.

For input datum x, suppose that its objective output is d, while actual output is y. In order to train networks, the mode pairs of train swatch are made up of $[x^k, y^k]$, and the superscript k is the serial number for a pair of train. And the front-propagation and back-propagation for every pair of swatch mode are dealt as follows.

3.1.1 Feed-forward front-propagation algorithm

When inputting datum $x(k)$ of the number k, the total inputs of node h in the hidden layer is

$$S_h(k) = \sum_i x_i(k) \cdot w_{ih} \tag{1}$$

Using Sigmoid activation function to deal with the relationship between inputs and outputs, then the output of the node h in hidden layer is

$$y_h(k) = \frac{1}{1 + e^{-\sum x(k) \cdot w}} \tag{2}$$

Accordingly, the output of the node j in the output layer is

$$y_j(k) = \frac{1}{1 + e^{-\sum y(k) \cdot w}} \tag{3}$$

If taking the total square error of all output nodes for k inputs as training target of networks, then there will be

$$J(w) = \frac{1}{2} \sum_k \sum_j [d_j(k) - y_j(k)]^2 \tag{4}$$

Since the transferring function (Sigmoid function) is continuous differentiable, so $J(w)$ is also obviously the continuous differentiable function to each weights.

3.1.2 Error back-propagation

Using gradient regulation, each w is differential to J, and it can get the gradient minimized J as the reversal of adjusting weights.

1) Adjust the weights w_{hj} from hidden layer to output layer, then

$$\Delta w_{hj} = -\eta \frac{\partial J(w)}{\partial w_{hj}} = \eta \sum_k \delta_j(k) \cdot y_h(k) \tag{5}$$

$$\delta_j(k) = [d_j(k) - y_j(k)] \cdot f'(S_j(k)) \tag{6}$$

2) Adjust the weights w_{hj} from input layer to hidden layer, then

$$\Delta w_{ih} = -\eta \frac{\partial J(w)}{\partial w_{ih}} = \eta \sum_k \delta_h(k) \cdot x_i(k) \tag{7}$$

$$\delta_h(k) = \sum_j w_{hj} \cdot \delta_h(k) \cdot f'(S_j(k)) \tag{8}$$

It usually adjusts the weights using current errors in actual application. In this way the summing item about k in Eqn.(5) and Eqn.(7) can be ignored. At one time in order to accelerate the training speed of network and improve its astringency, an impulsive item is appended during the weights adjusting. So the equations for weights adjusting are as follows.

For output layer:

$$\Delta w_{hj}(k+1) = \eta \delta_j y_h(k) + \alpha \Delta w_{hj}(k) \tag{9}$$

For input layer:

$$\Delta w_{ih}(k+1) = \eta \delta_h x_i(k) + \alpha \Delta w_{ih}(k) \tag{10}$$

where α is momentum factor or inertia factor; η is the learning rate; commonly α is 0.60~ 0.95 and η is 0.45~ 0.90.

3.2 Software realization of BP algorithm

The BP algorithm is actually designed to minimize the error function. By training the multi-learning sets again and again and using iterative gradient algorithm, it makes the weights change following the negative gradient direction of error function and converge to minimum. According to the principles of BP algorithm, a relevant realizable program based on MATLAB language is developed on computer.

4 STABLE FLOW STRESSES MODELS OF 1420 Al-Li ALLOY

4.1 Optimum design of network model

In the study, the neural network model of flow stresses has an input layer, a hidden layer and an output layer. According to the feature of high temperature compression deformation of alloys, the stable flow stresses are function of deformation strain, temperature and strain rate. So the network model, presented in Fig. 1, has three input variables in the input layer which are deformation strain ε, temperature T and strain rate $\dot{\varepsilon}$; while there is only one output vari-

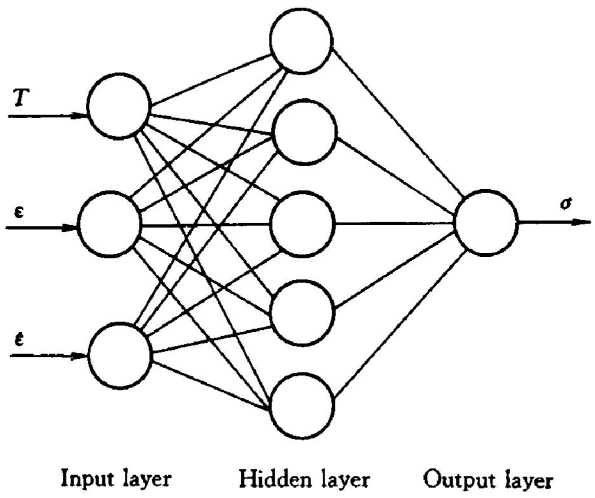

Fig. 1 Frame of neural network

able that is stable flow stress σ, and the neurons in the hidden layer take five[9].

4.2 Pretreatment of data

The data of deformation strains, temperatures and strain rates of 1420 Al-Li alloy at high temperature compression deformation were gathered. And in view of modeling training to actual deformation process there are generally various disturbing factors to the gained actual measuring data, so the gained data are divided into training sets and checking sets in order to let the developed model has extensive capacity.

At the same time, according to the demand of input-output range of BP network, the desired output values and the parameters in the input layer are normalized by Eqn. (11)[10]. It makes each eigenvariables to gain values between 0.1 and 0.9 in case that during network modelling iterative computing the numerical values excessively centralize on some neurons and weights which will recede the computing accuracy.

$$S_n = \frac{0.8(S - S_{\min})}{S_{\max} - S_{\min}} + 0.1 \qquad (11)$$

where S is input parameter as ε, T, $\dot{\varepsilon}$ and output value as σ for network; $S_{\min}$, $S_{\max}$ are maximum and minimum of relevant datum S.

4.3 Improvement of BP algorithm

Traditional BP algorithm has some disadvantages, such as long learning time and slow astringency of network. In order to reduce the iterative times in flat sections, accelerate astringency, avoid vibration and rapidly exit insensitive sections when local minimum during computing, some improvements are made based on traditional BP algorithm. Adopting batch manner to modify the conjunction weights of network model, namely, the total errors of system are computed after all of the learned sets are input. The weights are modified if the errors of system dissatisfy the demand in order to ensure the errors of system always changing toward the decreasing direction during learning, and pick up the convergent speed of system. Moreover, when computing the weights within (−1, +1) are adopted to be initialization range of weights.

4.4 Results and analyses

After the pretreatment of data being normalized, they are computed using BP algorithm programmed based on MATLAB language by the authors, and actual measured data and results predicted by model are shown in Table 3 and Table 4. Fig. 2 compares the values predicted by ANN and the true values, while Fig. 3 shows the relationship between values predicted by ANN and the actual values of stable flow stresses

Table 3 Actual values of stable flow stresses under various compression deformation conditions (ε = 0.5)

$\dot{\varepsilon}$/s^{-1}	σ/MPa				
	300 ℃	350 ℃	400 ℃	450 ℃	500 ℃
0.001	69.91	38.79	9.08	10.53	6.23
0.01	116.84	80.44	42.14	18.20	18.18
0.1	184.83	105.82	81.88	55.55	32.08
1.0	192.97	147.98	119.71	88.59	57.46
10.0	207.34	183.87	141.26	106.78	73.74
30.0	260.97	215.96	163.76	144.13	108.70

Table 4 Prediction values of stable flow stresses under various compression deformation conditions (ε = 0.5)

$\dot{\varepsilon}$/s^{-1}	σ/MPa				
	300 ℃	350 ℃	400 ℃	450 ℃	500 ℃
0.001	71.35	38.70	9.03	10.01	5.99
0.01	114.98	79.82	41.52	19.06	18.71
0.1	184.47	105.73	82.78	53.90	31.94
1.0	195.39	147.05	118.77	86.74	59.59
10.0	205.87	182.15	142.13	108.62	71.55
30.0	258.88	217.24	162.07	142.81	107.36

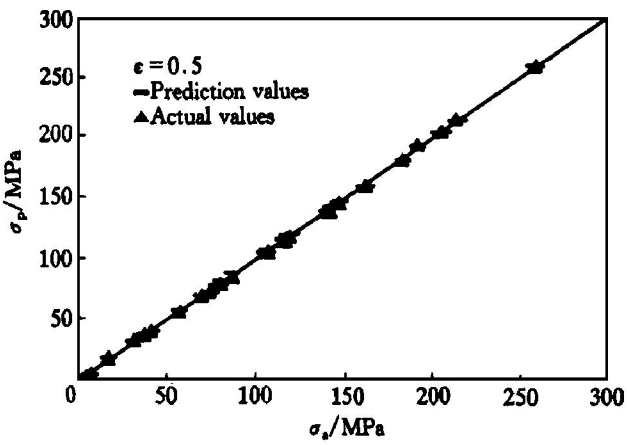

Fig. 2 Comparison between prediction values (σ_p) and actual values (σ_a) of Neural Networks

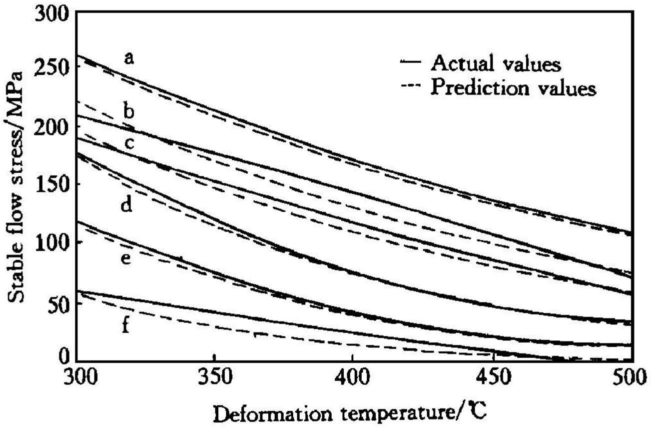

Fig. 3 Curves of prediction values and actual values vs temperature at different values of $\dot{\varepsilon}$
(a) —$\dot{\varepsilon}$= 30.0 s^{-1}; (b) —$\dot{\varepsilon}$= 10.0 s^{-1}; (c) —$\dot{\varepsilon}$= 1.0 s^{-1}; (d) —$\dot{\varepsilon}$= 0.1 s^{-1}; (e) —$\dot{\varepsilon}$= 0.01 s^{-1}; (f) —$\dot{\varepsilon}$= 0.001 s^{-1};

and deformation temperatures T and strain rates $\dot{\varepsilon}$.

The above results indicate that errors are within 5% when using developed network model to predict stable flow stresses which can absolutely satisfy the demands of computing in engineering and of actual deformation, while the calculational errors of traditional statistical models are up to 10%.

5 CONCLUSIONS

In the present study, the back-propagation Neural Network is used to develop the model of stable flow stresses for 1420 Al-Li alloy at high temperature compression deformation. Results of the investigation show that the method is effective and feasible. The neural network based model clearly indicates that it is able to learn of training data and accurately predict the unseen outputs.

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