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Constitutive model for ratcheting behavior of Z2CND18.12N austenitic stainless steel under non-symmetric cyclic stress based on BP neural network

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Abstract. The specimens made by Z2CND18.12N austenitic stainless steel were conducted on a 100 kN closed loop servo hydraulic tension-compression testing machine with a digital controller. Uniaxial tension and uniaxial ratcheting effect tests were carried out at 25℃. Moreover, Uniaxial tension tests were conducted at 150℃, 250℃ and 350℃. Based on these experimental data, the prediction models of stress-strain curve and the relationship of ratcheting strain and number of cycles were established by the algorithm principle of BP neural network. The results indicated that the predicted results of neural network model were in well agreement with experimental data. It was found that the BP neural network model had high validity and accuracy.

Keywords: BP neural network; constitutive relationship; Z2CND18.12N austenitic stainless steel; ratcheting strain; temperature

1. Introduction

Constitutive model of materials, was the function relationship of flow stress and hot working parameters, which represented the basic deformation behavior of materials (Yu and Chen 2005, Sumantra *et al*. 2009). The size of flow stress is the gist and precondition of the selection equipment, as well as the important symbol of the processing capacity of plastic materials. Understanding deformation characteristics of the materials under hot working conditions, the reference can be provided for the formulation of hot machining process. At the same time, the precision of constitutive model is directly affected the results of numerical simulation Accuracy. Therefore, the deformation behavior of materials at room and high temperature was researched, the control of metal material performance and the proper selection of process parameters had particularly important. Therefore, the basic mechanical properties of Z2CND18.12N austenitic stainless steel used by primary auxiliary straight piping loop of nuclear power plants were studied by means of experiments and BP neural network. Chen *et al*. (2016) studied ratcheting behavior of pressurized straight pipe and 90° elbow pipe subjected to reversed bending load at room temperature which were made of Z2CND18.12N austenitic stainless steel. But pressurized pipe in nuclear power plant worked at elevated and high temperature. Therefore, basic mechanical property of Z2CND18.12N austenitic stainless steel at elevated and high temperature was necessary.

Yu (2010) set up a new model for describing the uniaxial ratcheting behavior of Z2CND18.12N austenitic stainless steel based on Ohno-Wang II model, but the determination of model parameters is very complicated. Many scholars (Chen 2014) also use finite element software (ANSYS, ABAQUS, MARC and ADINA etc.) to establish different models of ratcheting effect (BKH, MKIN/KINH, CH3 and Ohno-Wang etc.), but these methods are very tedious and complicated, and the prediction accuracy is not enough. BP neural network, which was an important research achievement, had strong nonlinear reflection ability, redundant fault-tolerant ability and Fuzzy computing power. The constitutive relationship of material can be studied based on these characteristics of BP neural network. Guo *et al*. (2013) applied BP neural network in the continuous casting slab on-line diagnostics. Sample honogenized by custom functions and difference training algorithm can significantly improve the diagnostic accuracy rate; Selective training algorithm can speed up learning process, but also ensure the same diagnostic accuracy rate. The improved algorithm was in keeping with the real conditions of the continuous casting processes verified by the research result. Hakim and Abdul Razak (2013) examined a powerful tool for predicting the severity of damage in a model steel girder bridge. The data required for the Artificial Neural Networks (ANNs) which were in the form of natural frequencies were obtained from numerical modal analysis. By incorporating the training data, ANNs were capable of producing outputs in terms of damage severity using the first five natural frequencies. It had been demonstrated that an ANN trained only with natural frequency data can determine the severity of damage with a 6.8% error. Fotovati *et al*. (2014) proposed train artificial neural networks which was used to predict nanoindentation

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test results on different grain sizes of dual phase (DP) steels. The response of the ANN was analyzed in five case studies. Reliable and reasonable results of ANN predictions were achieved in each case. Jiménez-Come *et al*. (2015) proposed that used different classification models to predict the pitting corrosion status of AISI 316 L stainless steel according to the environmental conditions and the breakdown potential values. Based on recall and precision values, the most stable model was ANN-RB, performing with the highest classification success in most cases.

Based on any constitutive theory into a fully trained Artificial Neural Network, Stefanos and Gyan (2015) presented a methodology for converting or recasting complex constitutive models for geo-materials. Based on back propagation (BP) neural network, Lin *et al*. (2016) proposed a one-step-ahead model predictive control (MPC) strategy for the precise forging processes. Two online updated BP neural networks, predictive neural network (PNN) and control neural network (CNN), are developed to accurately control the die forging hydraulic press machine. It can be found that the proposed MPC strategy was the most effective control approach for the practical forging process. Zhou *et al*. (2015) used BP neural network model to optimize the settings of constitutive relations under different conditions of material strain rate forecast, and with the experimental values and modified J-C equation with modified to fit results than right. The results showed that BP neural network model to predict higher accuracy, prediction error and the measured value did not exceed 5%. BP neural network prediction model can be used to predict the material constitutive relations.

Based on BP neural network improved by genetic algorithm (GABP), Zhang *et al*. (2015) established a model to simulate the relation between welding appearance and the characteristics of the molten-pool-shadows. The effectiveness of the established model was analyzed through two different welding speed experiments, and the results verified its prediction performance. The work provided an effective way to predict the weld appearance and assess the welding quality in real-time. Based on the experimental data from the isothermal compressions of 42CrMo high strength steel, Quan *et al*. (2016) used artificial neural network to predict the elevated temperature deformation behavior of 42CrMo steel. The results indicated that the developed ANN model showed a good capacity of modeling complex hot deformation behavior and can accurately track the experimental data in a wide temperature range and strain rate range. Liu *et al*. (2016) employed Artificial Neural Network with double hidden layers composing of 10 neurons and 15 neurons to simulate the flow behavior of hot compression of the ZnCu2a110 alloy. The inputs of the model were temperature, strain and strain rate. The output of the model was the flow stress. The results indicated that the trained Artificial Neural Network model was a robust tool to predict the high temperature flow behavior of the ZnCu2a110 alloy. Based on the artificial neural network (ANN) of predicting the ultimate tensile strength of the API X70 steels, Khalaj *et al*. (2013) arranged in a format of seven input parameters that cover the chemical compositions, yield stress and Charpy impact energy, and output parameter which was ultimate tensile strength. The training, validation and testing results in the ANN had shown strong potential for prediction of relations between chemical compositions and mechanical properties of API X70 steels. Pouraliakbar *et al*. (2015a) and built an artificial neural network model with feed forward topology and back propagation algorithm to predict the toughness of high strength low alloy steels. Pouraliakbar *et al*. (2015b) and Khalaj *et al*. (2014) proposed artificial neural network models to predict the effect of chemical composition on material properties. Khalaj *et al*. 2014 and 2013 established models on basic of the GEP method to predict the layer thickness of duplex treated ceramic coating on tool steels and the relationship between the ultimate tensile strength and chemical composition of X70 steel.

In recent years, the artificial neural network models were considered as a powerful tool to describe the elevated temperature deformation behavior of materials. Constitutive model of titanium alloy was simulated by neural network which was widely applied by many researchers (Lu *et al*. 2010, Reddy *et al*. 2008, Su *et al*. 2010). But few constitutive relationships of other materials such as 316 stainless steel, 15 MnR were studied by BP neural network. Therefore, constitutive relationships of uniaxial tension and uniaxial ratcheting effect of Z2CND18.12N austenitic stainless steel were studied by experiments and BP neural network.

2. Experimental material and method

The material used in this study was Z2CND18.12N austenitic stainless steel. Chemical composition (wt%) of the material was C:0.0003, Cr: 0.1714, Ni: 0.1145, Si: 0.0037, Mn: 0.000164, S: 0.001, P: 0.0003, V: 0.00087, Mo:0.0 243, N: 0.00064.

The specimens were extracted from primary auxiliary straight piping loop of nuclear power plants. Tests were conducted on a 100 kN closed loop servo hydraulic tension-compression testing machine with a digital controller. Uniaxial strains were measured by an Epsilon extensometer with gauge length of 20 mm. Uniaxial tension was conducted at 25℃, 150℃, 250℃ and 350℃. Uniaxial ratcheting test was carried out at 25℃, considering the effect of mean stress and stress amplitude on ratcheting strain. For Z2CND18.12N austenitic stainless steel, many experimental data was given in the eferences (Yu *et al*. 2010, Liang 2014).

3. Neural network model of constitutive relationship

BP Neural network, was a large-scale distributed parallel processing system, which need not to know the complex change rule of input and output parameters, as given in Fig. 1. The given sample data was extracted from a mass of data, and then was first trained. A steady state of the network was formed in the form of a set of weights. The required data was obtained by means of associative memory and generalization ability.

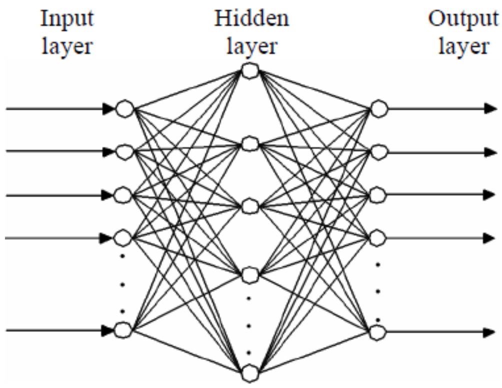


Fig. 1 Architecture of the BP ANN model

Constitutive relationship of Z2CND18.12N austenitic stainless steel was mainly the nonlinear relationship of stress versus strain for uniaxial tension test and the relationship of ratcheting strain versus number of cycles for uniaxial ratcheting effect test. Therefore, for uniaxial tension data under different temperatures, the stress was output parameter of neural network, strain and temperature were input parameters. For uniaxial ratcheting data, the ratcheting strain was output parameter of neural network, number of cycles, mean stress and stress amplitude were input parameters. The ranges of input and output parameters were required by neural network. Input parameters of input layer in the training pattern and stress value of output layer were regressed from obtained data, according to the following Eq. (1). The ranges of these parameters were between zero and one.

$$X' = \frac{X - 0.95X_{\min}}{0.5X_{\max} - 0.95X_{\min}} \tag{1}$$

where, the parameters X and X' were respectively the input and output parameters of the network. The parameters X_{max} and X_{min} were the maximum and minimum of the samples, respectively.

The architecture of hidden layer in BP neural networks had become a hot research issue, especially the number of hidden neurons in each layer. If the number of hidden neurons was too less, the trained network was not strong enough. Using too few neurons in the hidden layers will result in something called under-fitting. Under-fitting occurs when there are too few neurons in the hidden layers to adequately detect the signals in a complicated data set.

Using too many neurons in the hidden layers can result in several problems. First, too many neurons in the hidden layers may result in overfitting. Overfitting occurs when the neural network has so much information processing capacity that the limited amount of information contained in the training set is not enough to train all of the neurons in the hidden layers. A second problem can occur even when the training data is sufficient. An inordinately large number of neurons in the hidden layers can increase the time it takes to train the network. The amount of training time can increase to the point that it is impossible to adequately train the neural network. Obviously, some compromise must be reached between too many and too few neurons in the hidden layers. Ding *et al*. (2014) used the empirical formula to determine the number of neurons in the hidden layer of BP neural network, and then established the network model to predict the river water quality, which achieved the perfect prediction effect. Therefore, according to the actual operation, the optimal number of hidden neurons was determined by the following empirical formula.

$$n_1 = \sqrt{n+m} + a \tag{2}$$

where, the parameter n_1 was the number of hidden neurons. The parameter n was the number of output layer. The parameter m was the number of input layer. The parameter a was constant between 1 and 10.

Because of the elements of target vectors between 0 and 1, the transfer functions of input layer, hidden layer and output layer were set as 'tansig' and 'purelin'. The target error was 2×10-4, and target iteration steps was 10000. According to the above parameter setting, the BP neural network model was trained based on network architecture, finally target accuracy is achieved.

4. Results and discussion

4.1 Uniaxial tension model and analysis

4.1.1 Uniaxial tension under fixed temperatures

Programming with the "ANN TOOL" toolbox in MATLAB 2014a, the number of hidden neurons is preliminarily determined to be 10, and three different training functions are used to train the uniaxial tensile test data at 25℃, as shown in Fig. 2.

It is known from Fig. 1 and Table 1 that the trainlm

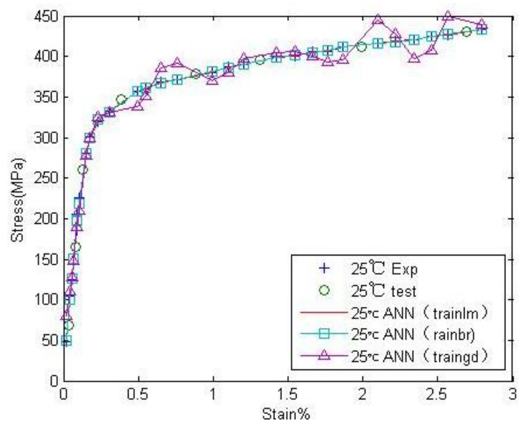


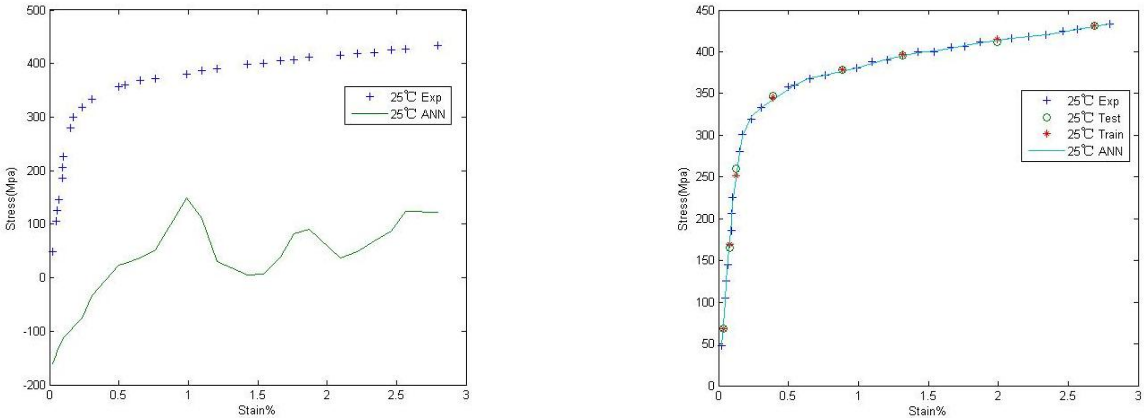
Fig. 2 Comparison of the results of different training functions at 25℃

Table 1 Comparison of error of training function

Train function	Trainlm	Trainbr	Traingd
Train error (1e-6)	3.57	3.3	56.93
Test error (%)	0.40	0.31	0.52

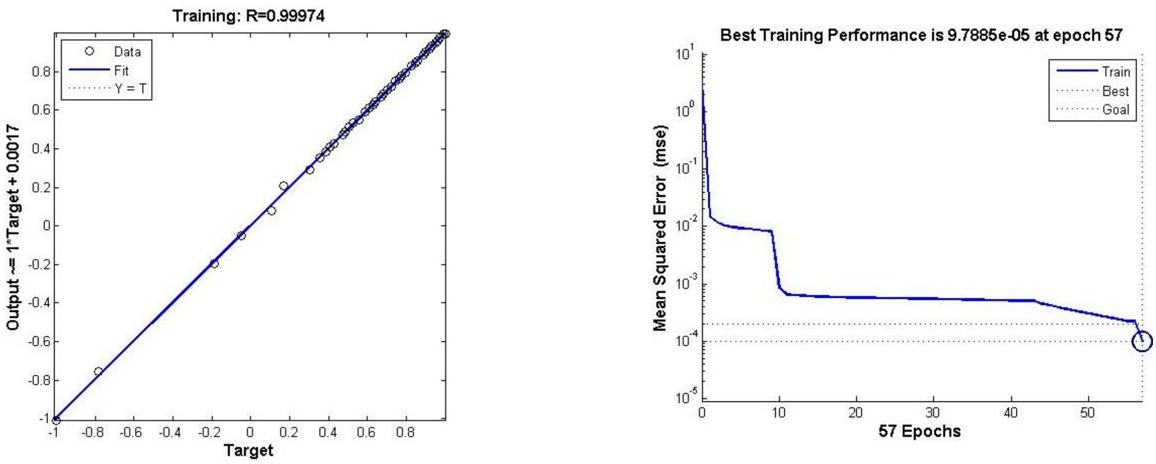
Table 2 Comparison of network training errors of different hidden neurons

Hide neurons	3	4	5	6	7	8	9	10	11	12
Train error (1e-6)	4.25	3.99	4.57	4.07	3.15	1.44	4.16	3.3	1.44	3.09
Test error (%)	0.32	0.32	0.31	0.31	0.30	0.31	0.29	0.31	0.28	0.27



(a) Before the training (b) After the training

Fig. 3 Comparison of experimental value with predicted value before and after the training



(a) Comparison of experimental value with predicted value (b) Training process error curve for neural network

Fig. 4 Accuracy and error

(Levenberg-Marquardt) and trainbr (Bias regularization algorithm) algorithm has less training error. The test error of the trainbr algorithm is far less than that of the trainlm algorithm. BP neural network model can have better generalization ability by using trainbr algorithm, so trainbr algorithm is used to train the neural network.

It can be seen from Table 2 that selecting the number of hidden neurons is 11 to make the model test error minimum. In order to the interpolation and extrapolation of neural network model, 20% data of uniaxial tension data at 25℃ were randomly selected as the detect data to inspect the predictive ability of network model. The neural network model was trained and tested based on the above parameters. Comparison of experimental value with predicted value for uniaxial tension before and after the training at 25℃ was shown in Fig. 3.

From Fig. 3, it’s known that the BP neural network model established in this paper can be well trained to predict the results of uniaxial tensile test at 25℃. Fig. 3(b) shows that the text data can fit well with the curve predicted by the BP neural network model. It indicates that the BP neural network model established in this paper has good generalization ability.

It can be seen from Fig. 4(a) that the straight slope of fitting scatter data is 0.99974 which coincides almost with the slope equal to 1. It indicates that constitutive relationship based on neural network, can well predict the uniaxial tension curve at 25℃, which has high accuracy. The learning curve can be a very good convergence in the test curve, as shown in Fig. 4(b).

Similar to neural networks, people often use SVM (Support Vector Machines) during data processing. This

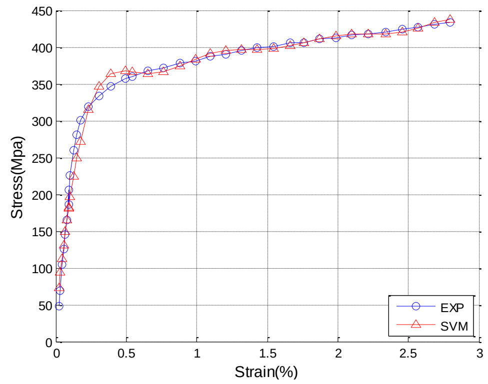


Fig. 5 Support vector machine model

Table 3 Comparison between SVM and BP NN model

Training algorithm	Fitting accuracy	Mean square error (1e-6)
BP NN	0.99974	1.44
SVM	0.98576	1242.45

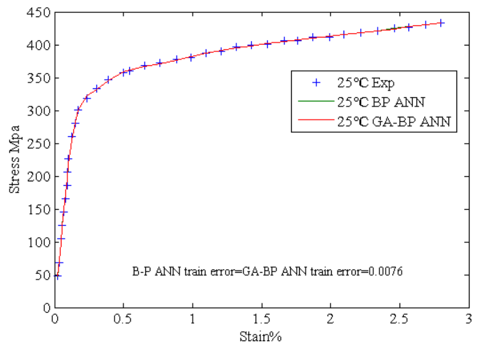


Fig. 6 Comparison of results before and after optimization of genetic algorithm

algorithm has advantages in solving small sample, nonlinear and high dimensional pattern recognition problems. So here we also use SVM to process uniaxial tensile sample data at 25℃, and compare the different results of the two algorithms to get the SVM model as shown in the Fig. 5.

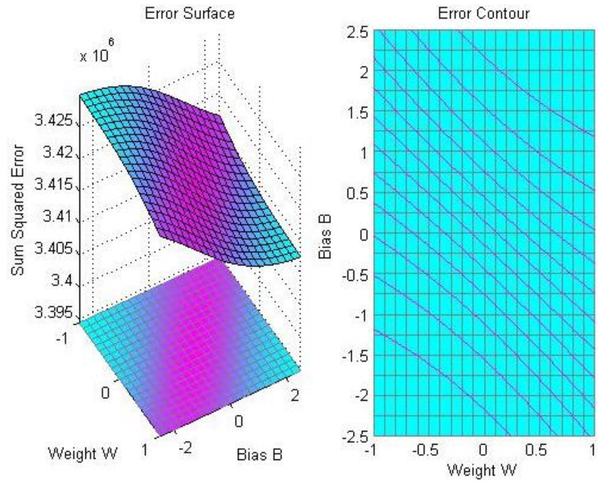


Fig. 7 Three-dimensional diagram of error

It can be seen from Fig. 5 that under the same conditions, the SVM model has a good fitting effect in the later stage, but a poor fitting effect in the early stage. The specific correlation and mean square error are shown in Table 3 below.

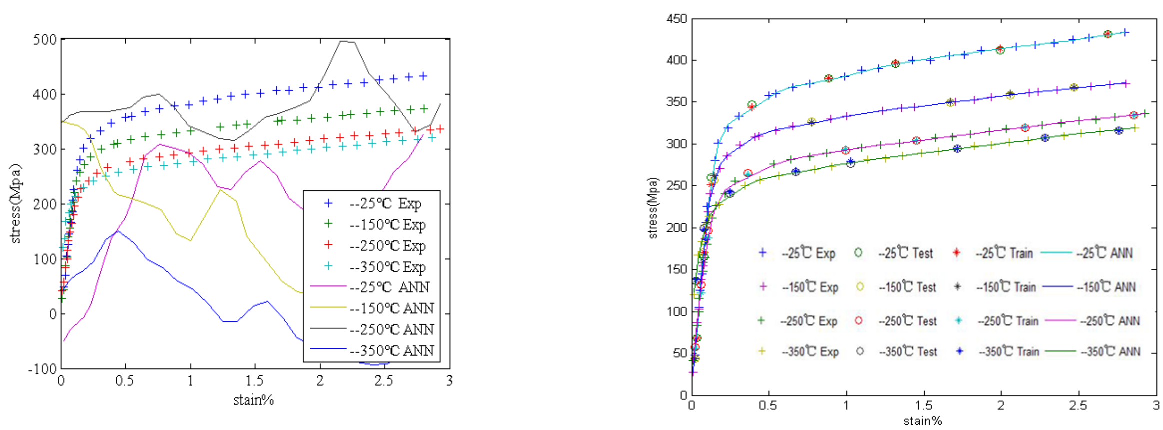
Can be seen clearly from the Table 3, the BP neural network is relative to the support vector machine (SVM) has better fitting effect, in order to further optimize the BP neural network, we use genetic algorithm to optimize the network, the optimization result is shown in Fig. 6.

From Fig. 6, the training accuracy of the network has reached the ideal result, and there is no local minimum. The advantage of genetic algorithm is not prominent, so the genetic algorithm is no longer used to optimize the network.

Fig. 7 shows three-dimensional diagram of error. It indicates the global error which can adjust weight threshold and optimize further neural network, but this article does not go into details.

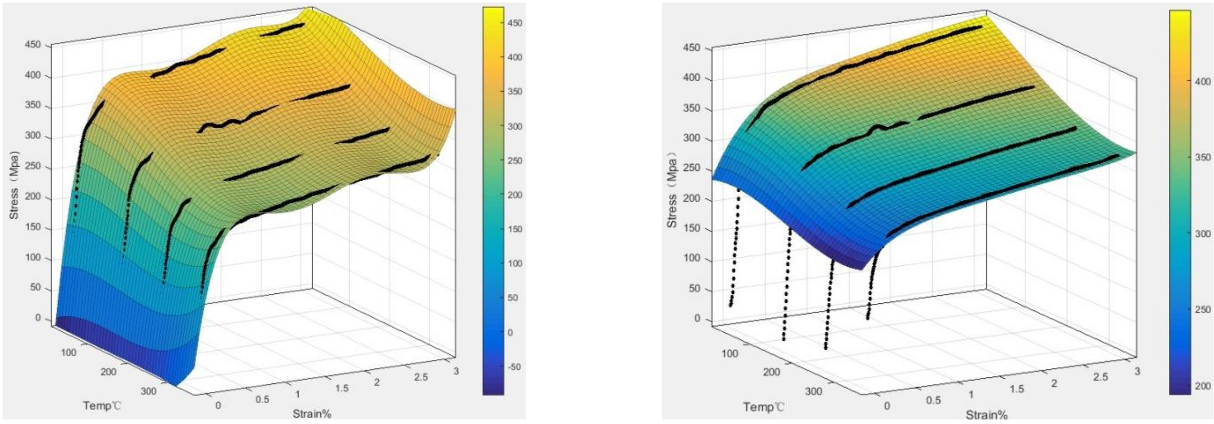
4.1.2 Uniaxial tension under different temperatures

Fig. 8 gave the comparison of experimental value with predicted value under different temperatures, namely 25, 150, 250 and 350℃. 20% data of uniaxial tension data under different temperatures were randomly selected as the



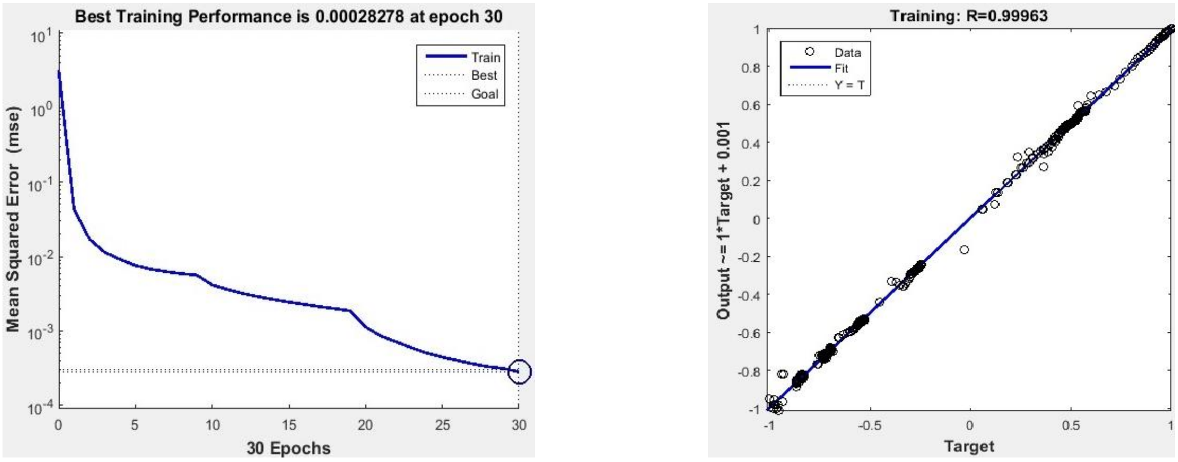
(a) Before the training (b) After the training

Fig. 8 Comparison of experimental value with predicted value under different temperatures



(a) (b)

Fig. 9 Prediction results in three dimensions of uniaxial tension of Z2CND18.12N austenitic stainless steel at different temperatures based on neural network



(a) Training process error (b) Comparison of experiment data with predicted value

Fig. 10 Precision graph of network training

detect data to inspect the predictive ability of network model. The results were given in Fig. 8. It was found from Fig. 8(a) that elastic modulus and yield stress of Z2CND18.12N austenitic stainless steel decreased with the increasing temperature, and tangent modulus was increased. It observed that the basic mechanical properties of Z2CND18.12N austenitic stainless steel was sensitive to temperature. It was found from Fig. 8(b) that the predicted results of network model were in well agreement with those of experiments.

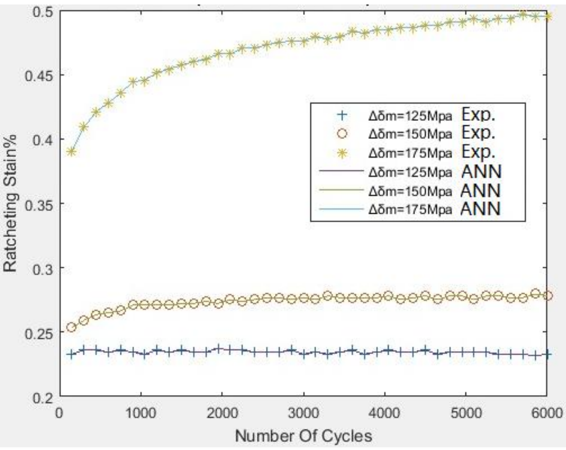
Fig. 9 indicated that prediction results in three dimensions of uniaxial tension of Z2CND18.12N austenitic stainless under different temperatures. It observed that neural network model can be well describe the relationship of uniaxial stress versus strain of Z2CND18.12N austenitic stainless under different temperatures, and the effect of temperatures on flow stress.

4.2 Uniaxial ratcheting strain

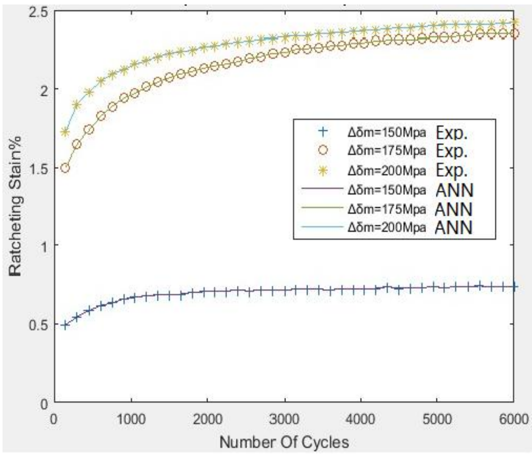
Uniaxial ratcheting strain of Z2CND18.12N austenitic stainless steel subjected to mean stress of 125 MPa and stress amplitude of 150 MPa was deeded as detect data. The learning curve can be a very good convergence in the test curve, as given in Fig. 10(a). It was seen from Fig. 10(b) that the straight slope of fitting scatter data was 0.99975 which coincided almost with the slope equal to 1. It indicated that constitutive relationship based on neural network, can well predict the relationship of uniaxial ratcheting strain and number of cyclic.

4.2.1 The effect of mean stress on ratcheting strain

Fig. 11 showed the effect of mean stress on uniaxial ratcheting strain of Z2CND18.12N austenitic stainless steel, and the comparison of predicted results of neural network model with experimental value. It gave that the evolution rule of ratcheting strain and number of cyclic was shown, ratcheting strain rate in original several cyclic was very larger, and then gradually tended to stabilize. Even ratcheting strain reached saturation values, namely shakedown. It was also found that ratcheting strain increased with increasing of mean stress. Meanwhile, there are good consistencies between the predicted results of neural network model and experimental value.

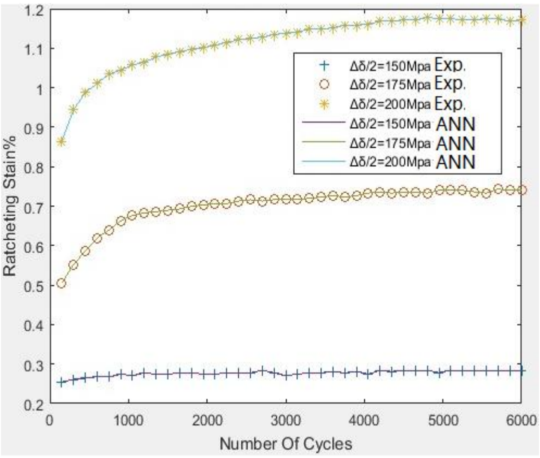


(a) Constant stress amplitude of 150 MPa

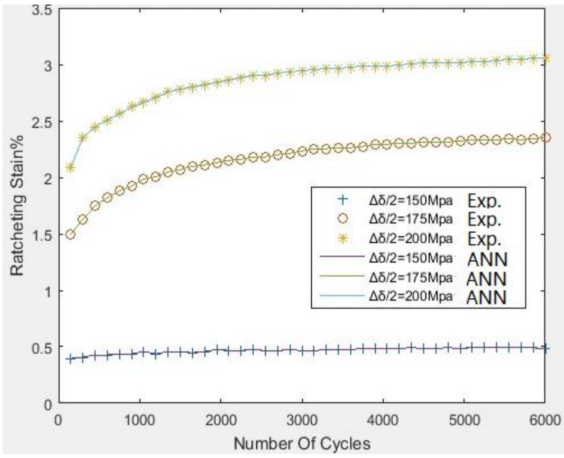


(b) Constant stress amplitude of 175 MPa

Fig. 11 The curves of ratcheting strain versus number of cycling with various mean stress and constant stress amplitude



(a) Constant mean stress of 150 MPa



(b) Constant mean stress of 175 MPa

Fig. 12 The curves of ratcheting strain versus number of cycling with various stress amplitude and constant mean stress

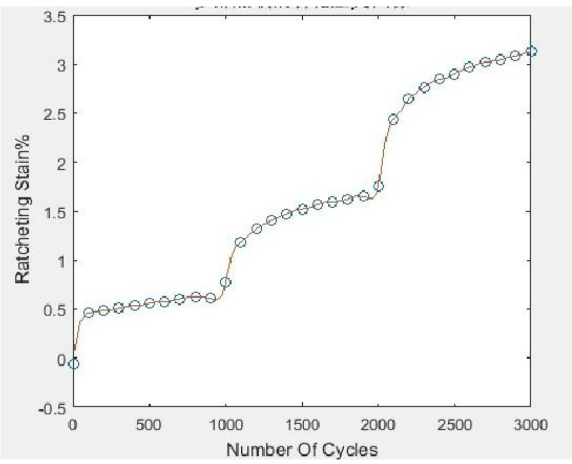


Fig. 13 The curve of ratcheting strain versus number of cycling with different mean stress and its history

4.2.2 The effect of stress amplitude on ratcheting strain

The effect of stress amplitude on uniaxial ratcheting strain of Z2CND18.12N austenitic stainless steel was shown in Fig. 12(a). It was also seen from Fig. 12(b) that the comparison of predicted results of neural network model with experimental value. The evolution rule of ratcheting strain and number of cyclic was given. It indicated that ratcheting strain increased with increasing of stress amplitude. Ratcheting strain rate in original several cyclic was very larger, and then gradually tended to stabilize. Even ratcheting strain reached saturation values, namely shakedown. Meanwhile, there are good consistencies between the predicted results of neural network model and experimental value.

4.2.3 The effect of loading history on ratcheting strain

The curve of ratcheting strain versus number of cycling with different various stress amplitude and constant mean stress and its history was given in Fig. 13, Namely under constant mean stress of 150 MPa and stress rate 100 MPa/s, stress amplitude was respectively 175 MPa, 200 MPa and 225 MPa. It was seen from Fig. 13 that ratcheting strain rate at first step (stress amplitude 175 MPa) was relative smaller, and that of second and third steps (stress amplitude 200 MPa and 225 MPa) increased very rapidly. Moreover, the predicted results of neural network model were good consistent with experimental value.

5. Conclusions

Based on uniaxial tension data at 25℃, 150℃, 250℃ and 350℃ and uniaxial ratcheting strain of Z2CND18.12N austenitic stainless steel subjected to non-symmetric cyclic stress, the constitutive relationship of neural network was used in this study. Strains and temperatures for uniaxial tension at different temperatures were input parameters, respectively, and out parameter was stresses. For uniaxial ratcheting behavior, number of cyclic, mean stress and stress amplitude were respectively input parameter, and ratcheting strain was output parameters. After the neural network model was trained, the correlation coefficients of the results of the neural network model and experiments were almost 1. The results observed that predicted results of neural network model were in well agreement with those of experiments. The neural network model has high accuracy, which can well reflect the basic mechanical behaviors of Z2CND18.12N austenitic stainless steel.

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