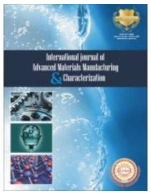

Advanced Materials
Manufacturing & Characterization

journal home page: www.ijammc-griet.com

Prediction of Deformation Behavior of Austenitic Stainless Steel 304 in Dynamic Strain Aging Regime

Nitin Krishnamurthy[1], Yashjeet Singh[1], A K Gupta[1], S K Singh[2]

[1]Department of Mechanical Engineering, BITS-Pilani, Hyderabad Campus, Hyderabad – 500078
[2]Department of Mechanical Engineering, GRIET, Hyderabad – 500090

A R T I C L E   I N F O

Article history:
Received 10 Nov2012
Accepted 26 Dec 2012

Keywords:
Austenitic Stainless Steel,
Flow Stress,
Constitutive model, Zerilli Armstrong model,
Artificial Neural Networks

A B S T R A C T

The main focus of this paper is prediction of flow stress of Austenitic Stainless Steel 304 in the Dynamic Strain Aging (DSA) regime. For this purpose, a comparative study has been made on the capability of modified Zerilli Armstrong (ZA) model and the Artificial Neural Networks (ANN) model for representing the flow stress prediction in the DSA Regime. The DSA regime was identified by observing the serrations in the plot between true stress and true strain.The modified-ZA equation for prediction of flow behavior at elevated temperature of the material considers isotropic hardening, temperature softening, strain rate hardening, and the coupled effects of temperature and strain and of strain rate and temperature on the flow stress. Artificial Neural Network is another powerful tool to predict the flow stress behavior which uses a part of the data to train the network while the other is used to validate the model. Suitability of these models was evaluated by comparing the correlation coefficient and absolute average error of prediction. It was observed that the flow stress predictions of ZA model were not as accurate as compared to predictions of ANN model. The resultant value of the correlation coefficient for ZA Model was 0.8889 and that of ANN's tested data was 0.9990.

Introduction

Austenitic Stainless Steel 304 has found various applications in the field of defense and nuclear science because of its excellent corrosion resistance in saline environment due to the presence of molybdenum which prevents chloride corrosion. It is also used for cladding of fuel rods in nuclear reactors. It has low carbon content which means less carbide precipitation in the heat-affected zone during welding and a lower susceptibility to intergranular corrosion. It was reported low carbon steel exhibited greatly improved wear and friction properties [1].For this type of steel, it was observed that at elevated temperatures and specific strain rates under tensile load, the phenomenon of Dynamic Strain Aging (DSA) occurred. At elevated temperatures, the mobility of solute atoms can become large enough that they can follow a dislocation during its motion and segregate to its core while it has to wait in front of an obstacle. The repeated segregation and detachment process causes the flow stress to oscillate. In such cases, serrations i.e., a wavy pattern like saw teeth in the stress-strain plot are observed. This effect is called Dynamic Strain Aging or Portevin–Le Chatelier (PLC) effect. DSA occurs for certain range of temperatures and strain-rates. [2]Constitutive equations, which represent the material's flow stress behaviour, are used in FEM softwareto model the material's behavior under specified loading conditions. Hence, the accuracy of the numerical simulation in FEM is mainly dependent on accuracy of these constitutive equations in representing the deformation behavior of the material. In the recent past, several constitutive models have been developed which can be broadly classified into three categories, namely phenomenological constitutive models, physical based constitutive models and artificial neural networks [3]. The experimental stress–strain data from isothermal hot tensile tests over a wide range of temperatures, strains and strain rates are being employed to formulate suitable constitutive models (modified ZA and ANN models) to predict the elevated temperature deformation behavior.

- Corresponding author: A K Gupta
- E-mail address: akgupta@bits-hyderabad.ac.in
- Doi: http://dx.doi.org/10.11127/ijammc.2013.02.025

Experimental Details

Flat tensile test specimens of austenitic stainless steel 304 sheet with 0.9 mm thickness were used to perform the experiments. The dimensions were as per Defence Metallurgical Research Laboratory, Hyderabad (DMRL) standards. The composition of the material used is given in Table 1. The samples were machined out of raw sheet material by wire-cutting electro-discharge machining process for high accuracy and finish. Isothermal tensile tests were carried out to determine the flow stress behavior as well as study the dynamic strain aging phenomenon.

Figure 1 shows the computer controlled Universal Testing Machine (UTM) having maximum load capacity of 100 KN that was used to conduct the tests. This machine is equipped with a controlled system to impose exponential increase of the actuator speed to obtain constant true strain rates. The Figure also shows the resistance heating three zone split furnace used to heat the tensile test specimen up to 1000 0C. The pull rods for the high temperature testing at UTM are made of Nickel base super alloy CM-247.

The experiments were conducted at four different strain rates (0.0001, 0.001, 0.01 and 0.1s−1) and various temperatures ranging from 623K to 923K at an interval of 50K. A computer control system is used to record the load versus displacement data, which were converted into true stress versus true plastic strain curves. From the data obtained, it was observed that the DSA phenomenon occurred at lower strain rates (0.0001, 0.001 and 0.01s-1) and higher temperatures (723-923K) .

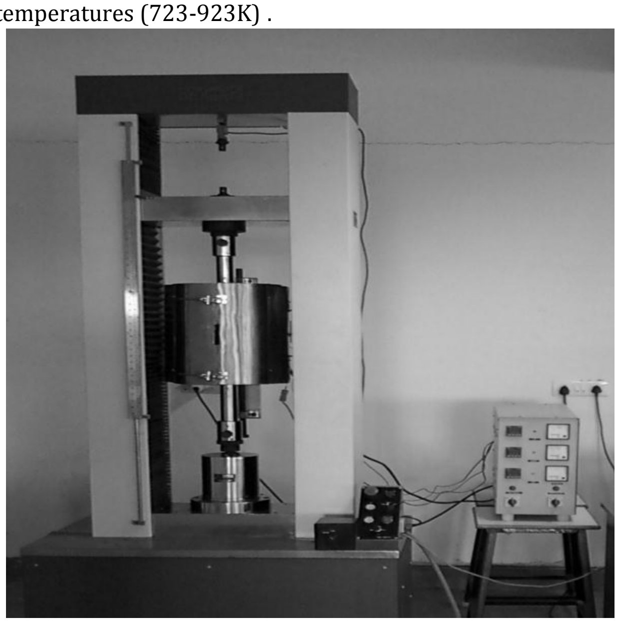

Figure 1: Computer controlled UTM of 100kN capacity with Resistance heating three zoneSplit Furnace

Table 1: Chemical composition of Austenitic stainless steel 304 *(wt. %)*

Element	**Fe**	**C**	**Mn**	**Si**	**Mo**	**Co**	**Cr**	**Cu**	**Ni**	**Others**
Composition (%)	70.780	0.025	1.140	0.410	0.360	0.210	18.400	0.180	8.190	0.305

Development of constitutive equations

Modified – Zerilli – Armstrong (ZA) Model:

According to original ZA model [4], the flow stress is expressed as:

$$\sigma = A_0 + A_1\varepsilon^n \exp((-A_2T) + (A_3T \ln \dot{\varepsilon}))$$

where σ stands for flow stress, ε for equivalent plasticstrain, $\dot{\varepsilon}$ for strain rate, T for absolute temperature, A_0 isthe athermal component of yield stress, and A_1, A_2, A_3 and n are the material parameters.Flow stress is divided intwo components component by this model i.e. thermal and athermal.

It can be inferred from the Figure 2that yield stress of Austeniticstainless steel 304 decreases with increase in temperature. So, in the proposed Modified ZA model (as discussed below), athermal component ofthe flow stress is neglected.

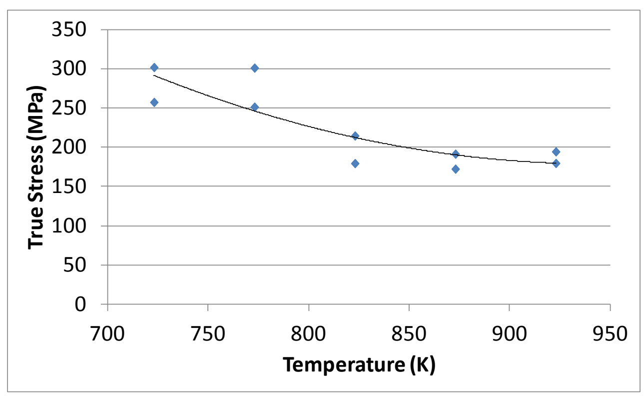

Figure 2: Plot of true stress and temperature at 0.0001 s-1 strain rate for modified ZA model.

A modified constitutive model, based on Zerilli-Armstrong (ZA) model has been formulated to predict flow stress behavior of materials at elevated temperatures [5]. This model is represented by Eq. 1:

$$\sigma = (C_1 + C_2\varepsilon^n) \exp\{-(C_3 + C_4\varepsilon) T^* + (C_5 + C_6T^*) \ln \dot{\varepsilon}^*\} \quad (1)$$

where σ stands for flow stress, ε is the equivalent plastic strain, $\dot{\varepsilon}^* = \dot{\varepsilon}/\dot{\varepsilon}_0$ is the dimensionless strain rate with $\dot{\varepsilon}$

being the strain rate and $\dot{\varepsilon}_0$ being the reference strain rate ($\dot{\varepsilon}_0$ is taken as 0.01s-1 i.e. highest strain rate among all strain rates of experiments) and T^* = (T - Tref), where T is current temperature, Tref is reference temperature (Tref is taken as 723K i.e. lowest temperature among all temperatures of experiments) and $C_1, C_2, C_3, C_4, C_5, C_6$, n are material constants.

The modified - ZA equation considers the phenomena of isotropic strain hardening, temperature softening, strain rate hardening, and the coupled effects of temperature, strain and of strain rate while predicting the flow stress at higher temperature. Procedure to evaluate the material constants for Modified - ZA model is as discussed below:

Condition 1: Reference Strain rate

At $\dot{\varepsilon}_0$ = 0.01s-1, i.e. when $\dot{\varepsilon}^*$ = 1 Eq. (1) can be expressed as:

$$\sigma = (C_1 + C_2\,\varepsilon^n)\exp\{-(C_3 + C_4\varepsilon)T^*\} \qquad (2)$$

Taking natural logarithm on both sides of Eq. (2), we get:

$$\ln\sigma = \ln(C_1 + C_2\varepsilon^n) - (C_3 + C_4\varepsilon)T^* \qquad (3)$$

From Eq. (3), it is seen that the plot $\ln\sigma$ vs T^*has the slope S1 = -$(C_3 + C_4\varepsilon)$ and intercept as$\ln(C_1 + C_2\varepsilon^n)$. For each strain, we get a particular value of slope and intercept. Let I be the intercept. Then, I is given by Eq. (4)

$$I = \ln(C_1 + C_2\varepsilon^n) \qquad (4)$$

Taking exponential and then logarithm on both sides of Eq. (4), we get:

$$\ln(\exp(I) - C_1) = \ln(C_2) + n.\ln(\varepsilon)$$

C1 is obtained as the yield stress from the experiment conducted at reference temperature and reference strain rate. Plotting $\ln(\exp(I) - C_1)$ vs $\ln(\varepsilon)$ after substituting C_1= 209.696 Mpa, we get the slope n and the value of C2 from the intercept. Similarly, by plotting S1 vs.ε we get the values of C_3 and C_4 from the slope and intercept of the curve.

Condition2: Considering coupled effects

For this condition, taking the natural logarithm of Eq. (1) yields:

$$\ln\sigma = \ln(C_1 + C_2\,\varepsilon^n) - (C_3 + C_4\varepsilon)T^* + (C_5 + C_6T^*)\ln\dot{\varepsilon}^*$$

The $\ln\sigma$ vs $\ln\dot{\varepsilon}^*$plot has slope S2 and this slope can be represented as Eq. 5,

$$S_2 = (C_5 + C_6T^*) \qquad (5)$$

For five different temperatures, five different values of S2 are obtained at a particular strain. From the plot S_2 vs T^* values of C5 and C6 are obtained. So, total 15 different values of C5 and C6 are obtained at different strains. These values are optimized to minimize error using constrained optimization as discussed below.

Constrained Optimization

To obtain final values of material constants C5 and C6, from 15 different values, the method of least squares is used. This procedure involves the constrained optimization of the values by minimizing the average absolute errors (Δ) between the experimental (σexp) and predicted flow stress (σp). Its equation is given by:

$$\Delta = \frac{1}{N}\sum_{i=1}^{i=N}\left|\frac{\sigma^i_{\exp} - \sigma^i_p}{\sigma^i_{\exp}}\right| \times 100$$

where, σexp is the experimental flow stress, σp is the predicted flow stress and N is the total number of data points being considered. The predictability of the constitutive equation is also quantified by employing standard statistical parameters such as correlation coefficient (R) and average absolute error (Δ). Correlation coefficient is a commonly used statistical tool which provides information on the strength of linear relationship between the experimental and predicted values. It can be mathematically expressed as:

$$R = \frac{\sum_{i=1}^{i=N}(\sigma^i_{\exp} - \overline{\sigma_{\exp}})(\sigma^i_p - \overline{\sigma_p})}{\sqrt{\sum_{i=1}^{i=N}(\sigma^i_{\exp} - \overline{\sigma_{\exp}})^2 \sum_{i=1}^{i=N}(\sigma^i_p - \overline{\sigma_p})^2}}$$

where, $\overline{\sigma_{\exp}}$ and $\overline{\sigma_p}$ are the average values of $\sigma_{\exp}$ and σ_p respectively. Although the value of R might be high, it isn't necessary that the performance of the model is high as the model might have a tendency to be biased towards higher values or lower values of the data [6]. Hence, Δ, which is computed through a term by term comparison of the relative error, is an unbiased statistics for measuring the predictability of the model [7]. Calculations have been performed on MATLAB. The parameters for the modified -ZA ModelarementionedinTable2

Table 2: Material constants obtained for modified ZA model after constrained optimization

Parameter	C_1 (Mpa)	C_2 (Mpa)	C_3	C_4	C_5	C_6	N
Value	209.696	1463.1	0.000475	0.0049	-0.0386	0.0010	0.9231

Artificial Neural Networks (ANN)

Artificial Neural networkis a recently developed artificial intelligence technique, which is being used for prediction of flow stress at elevated temperatures. This technique emulates the biological neural systems behavior in digital software or hardware. There is no need to define an algorithm or process to convert and input to output. This method is very useful in processes where the physical mechanisms are quite difficult, sometimes impossible to understand completely. It also used for processes where there is no satisfactory analytical or physical model. The greatest advantage of ANN is that it has the ability to use an arbitrary function approximation mechanism that 'learns' from the observed data. The ANN then adapts itself to reproduce the desired output when it is presented with training sample input. ANN is ideally suited for prediction of flow stress from the experimental data because of its high parallelism. As mentioned, this model does not require explicit mathematical and physical knowledge if deformation mechanism. To understand the flow stress behavior in the DSA regime, ANN modeling is easier as compared to modelling by constitutive equations.

Each neural network is composed of three layers: an input layer, an output layer and one hidden layer, which are connected by the processing units called neurons. Each neuron has an associated transfer function and works as an independent processing element. This transfer function describes the conversion of weighted sum of its inputs into an output value. There are many training algorithms available, but in our case an ANN with back propagation algorithm is adapted for prediction of flow stress. Back propagation algorithm is based on minimization of the quadratic cost function by tuning the network parameters. Hence, the mean square error (MSE) is considered as a measurement criterion for a training set. [2]

For this case, there are three input variables viz. strain rate, deformation temperature and strain while the outputvariable is flow stress value. Before training the network, it is important to normalize the input and output data within range of 0.05-0.95 to prevent any specific factor from dominating the learning for ANN model and to make the neural network training more efficient. This is also done to recast them in to dimensionless units as the variables are measured in different units.The experimental data was normalized using Eq. (6)

$$x_n = 0.05 + 0.90^*(x - x_{min}/x_{max} - x_{min}) \qquad (6)$$

wherexmin and xmax are the minimum and maximum values of x and xn is the normalized data of the corresponding x. Once the best trained network is found, all the transformed data returns to their original value using Eq. (7)

$$x = x_{min} + (x_n - 0.05) * (x_{max} - x_{min})/0.90 \qquad (7)$$

The next step is to decide the ANN architecture, which requires choosing appropriate number of hidden units. The number of hidden layers determines the complexity of neural network. Having more number of hidden layers causes over fitting of data. A desirable network should have minimum number of hidden layers for good approximation of the true function. To determine the optimum number of hidden layers, the mean square error for
various numbers of hidden layers were examined. It was observed the mean square error decreases to minimum value when 8 neurons are selected as shown in Figure 3 (a). Although increasing the number of neurons decreases the mean square error, only 8 intermediate neurons are selected to avoid over fitting.

Hence, the developed ANN architecture consists of an input layer containing three neurons, a hidden layer containing 8 intermediate neurons and an output layer containing one neuron as shown in Figure 3 (b). The hidden layer uses a hyperbolic tangent sigmoid (tansig) transfer function, while the output layer uses a linear (purelin) transfer function to map the output parameters.

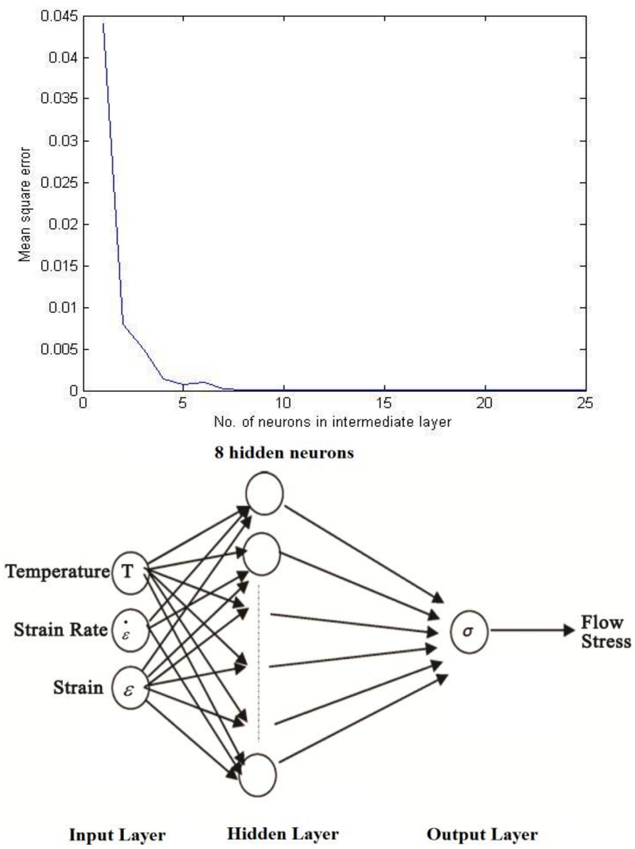

Figure 3: (a) Plot of mean square error (MSE) vs. no. of intermediate neurons in the ANN architecture, (b) ANN architecture (3-8-1)

The experimental data consisted of 225 data points which were used for training the network using Levenberg – Marquardt function (trainlm). 10% (22) of the data was used as a testing data while the remaining 90% (203) was used to train the model. These data were chosen randomly using in built functions of MATLAB. The neural network toolbox of MATLAB software package is used for training and testing the given data.

Results and discussion

The equation for modified-ZA model is given by

$$\sigma = (209.696 + 1463.1\varepsilon^{0.9231}) \exp\{-(0.000475 + 0.0049\varepsilon)T^* + (-0.0386 + 0.0010)\mathrm{T}^*) \ln \dot{\varepsilon}^*\}$$

The value of material constant C_5 obtained is negative, as shown in Table 2, which indicates negative strain rate sensitivity. This is one of the major reasons for occurrence of DSA. For this model, R was 0.8889 shown in Figure 4 and Δ was 14.3916%. The modified ZA model is particularly not suitable to represent the flow behaviour of material at temperatures above $0.6T_m$ and lower strain rates. For austenitic stainless steel 304, the melting temperature is 1673. So 0.6Tm=1000K. Although, in the present work experiments were carried out at temperatures lower than 1000K, but the strain rates were low. Hence, the predictions of modified ZA model were not efficient. The ANN model gave a correlation coefficient of 0.9990 shown in Figure 5 and average absolute error(Δ) value of 1.3746% which indicates an excellent correlation between experimental and predicted flow stress values. The results imply that for austenitic stainless steel 304, the developed ANN model is consistent with what is expected from fundamental theory of hot deformation. This suggests that the model possesses excellent capability to predict the flow softening stages and strain hardening, especially in the DSA regime. ANN model can be applied to serrated flow and mechanical properties can be predicted very accurately if sufficient input data is recorded in the DSA region by experiments. Hence, ANN model can be suitably used to predict the flow stress values in DSA regime.

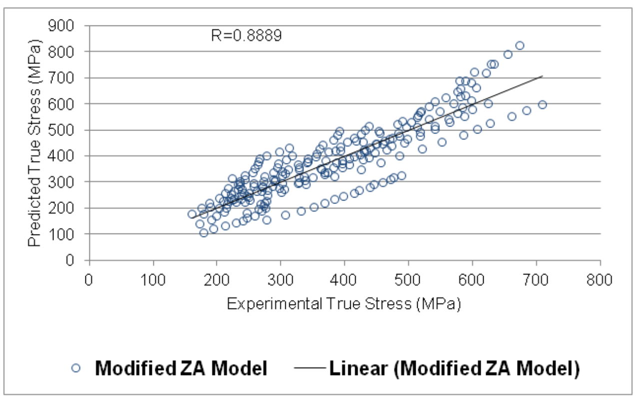

Figure 4: Plot of predicted vs experimental stress for Modified - ZA Model.

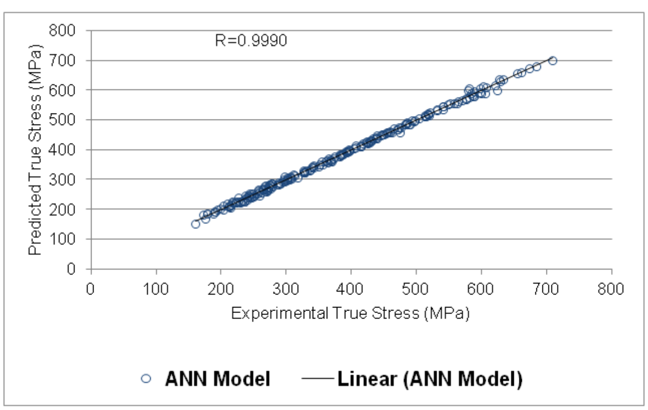

Figure 5: Plot of predicted vs experimental stress for ANN Model.

Conclusion

The value of flow stress depends on three parameters, namely, strain, strain rate and temperature. At elevated temperature and lower strain rates, the phenomenon of Dynamic Strain Aging (DSA) occurs. In this paper, a comparative study was done to evaluate the capability of the modified ZA and ANN models to predict the flow stress values in DSA regime. It was found that ANN model provided the best prediction. But, presently the limitation of this model is that it cannot be incorporated into any FEM software. Hence a physical model (modified ZA) was analyzed, which can be easily incorporated into FEM software. As the predictions of this model were not in-tune with the experimental data, further studies towards the development of an extensive model which can be incorporated into FEM software to capture the DSA region are due.

Acknowledgments: The financial support received for this research work from Department of Atomic Energy (DAE), Government of India, through Young Scientist Research Award 2009/36/45-BRNS/1751 is gratefully acknowledged.

References

1. Wang X.Y., Li D.Y. Wear. Mechanical, electrochemical and tribological properties of nano-crystalline surface of 304 stainless steel. (2003), 255:836:845
2. Gupta A.K. et al., Prediction of flow stress in dynamic strain aging regime of austenitic stainless steel 316 using artificial neural network.Materials and Design (2012) 35:589–595.
3. Y.-C. Lin, X-M. Chen, Materials and Design 32(2011) 1733-1759.
4. [F.J. Zerilli, R.W. Armstrong, Journal of Applied Physics 61 (1987) 1816–1825.
5. Samantaray D. et al., A comparative study on Johnson Cook, modified Zerilli–Armstrong and Arrhenius-type constitutive models to predict elevated temperature flow behaviour in modified 9Cr–1Mo steel. Computational Materials Science (2009)47:568-576
6. Phaniraj M.P., Lahiri A.K, The applicability of neural network model to predict flow stress for carbon steels. J.Mater. Process Technol.(2003)141:219-227
7. Srinivasulu S., Jain A., A comparative analysis of training methods for artificial neural network rainfall–runoff models. Appl.SoftComput.(2006)6:295-306