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Prediction of flow stress in dynamic strain aging regime of austenitic stainless steel 316 using artificial neural network

Amit Kumar Gupta [a,*], Swadesh Kumar Singh [b], Swathi Reddy [c], Gokul Hariharan [d]

[a] Department of Mechanical Engineering, BITS-Pilani, Hyderabad Campus, AP 500 078, India
[b] Department of Mechanical Engineering, GRIET, Bachupally, Hyderabad, AP 500 072, India
[c] Research Scholar, Material Science and Engineering, University of New South Wales, Sydney 2052, Australia
[d] Department of Chemical Engineering, NIT, Warangal, AP 506 004, India

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ABSTRACT

Flow stress during hot deformation depends mainly on the strain, strain rate and temperature, and shows a complex nonlinear relationship with them. A number of semi empirical models were reported by others to predict the flow stress during deformation. In this work, an artificial neural network is used for the estimation of flow stress of austenitic stainless steel 316 particularly in dynamic strain aging regime that occurs at certain strain rates and certain temperatures and varies flow stress behavior of metal being deformed. Based on the input variables strain, strain rate and temperature, this work attempts to develop a back propagation neural network model to predict the flow stress as output. In the first stage, the appearance and terminal of dynamic strain aging are determined with the aid of tensile testing at various temperatures and strain rates and subsequently for the serrated flow domain an artificial neural network is constructed. The whole experimental data is randomly divided in two parts: 90% data as training data and 10% data as testing data. The artificial neural network is successfully trained based on the training data and employed to predict the flow stress values for the testing data, which were compared with the experimental values. It was found that the maximum percentage error between predicted and experimental data is less than 8.67% and the correlation coefficient between them is 0.9955, which shows that predicted flow stress by artificial neural network is in good agreement with experimental results. The comparison between the two sets of results indicates the reliability of the predictions.

1. Introduction

Austenitic stainless steel 316 has been increasingly and extensively applied in the field of nuclear applications because of its excellent corrosion resistance in seawater environment due to having addition of molybdenum which prevents chloride corrosion. This steel is very useful in nuclear applications – particularly for cladding of fuel rods in the nuclear reactors. At elevated temperatures for specific strain rates under tensile load, the phenomenon of Dynamic Strain Aging (DSA) has been observed in this material. DSA is characterized by serrated stress–strain curve, i.e., wavy pattern like saw teeth on stress–strain curve. This is also called as Portevin-Le Chatelier (PLC) effect. This is due to the diffusion of solute atoms into mobile dislocations which temporarily get arrested at obstacles. The solute atoms are able to diffuse at a rate faster than the speed of the dislocations to catch and lock them. Therefore, due to the locked dislocations the load increases and when the dislocations are annihilated from the solute atoms, there is a sudden load drop. This process occurs many times, which causes serration in the stress–strain curve. Thus, DSA is manifested by a negative strain rate sensitivity, which results in unstable, jerky flow. DSA occurs for certain range of temperatures and strain-rates. A critical strain rate is required for serrated yielding to take place in a particular temperature range. This temperature range is called blue brittle region because metal heated to this temperature region shows a decrease in ductility and notch impact resistance. A widely accepted consequence of DSA is the negative strain rate sensitivity that is observed for many alloys.

Several researchers have studied the behavior of austenitic stainless steel under tension test to investigate the effect of temperature and strain rate on its mechanical properties [1–4]. Kaiping et al. [1] studied the serrated flow behavior of austenitic stainless steels in the different ranges of 523–673 K and 723–873 K at the strain rates of $5 \times 10^{-4}\,s^{-1}$. For these temperature–strain-rate combinations, a slow decrease in ultimate tensile strength and the negative strain rate sensitivity have been observed, which indicates the presence of DSA phenomenon in the material. The DSA pre-treatment can effectively improve the creep strength and the short-time tensile strength at high temperatures. Samuel et al. [2] observed increase in the ductile fracture resistance of titanium

* Corresponding author. Tel.: +91 40 66303518; fax: +91 40 66303998.
E-mail address: akgupta@bits-hyderabad.ac.in (A.K. Gupta).

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Table 1
Chemical composition of austenitic stainless steel 316 (wt.%).

Element	Fe	Cr	Ni	Mo	Mn	Si	Co	Cu
Composition (%)	67.690	16.630	10.850	2.420	1.280	0.380	0.210	0.210

Fig. 1. A computer controlled UTM with a high temperature chamber.

modified stainless steel due to DSA. The strengthening effect of DSA pre-treatment is much better than traditional cold-working pre-treatment. In a large number of metals and alloys, the DSA phenomenon alters the flow stress behavior of the metal and even it may cause the formation of flow-localized regions during deformation due to the negative strain rate sensitivity [5,6].

The flow stress during the hot deformation is influenced by many factors such as strain, strain rate and temperature etc. Due to the complex interconnections among these parameters and materials properties, mathematical models are sometimes very complex to handle by the numerical techniques as well as by experimental methods, especially when it involves some particular material phenomenon such as DSA. Considerable amount of work were done in past few decades to correlate the flow stress with the process parameters through the constitutive and the empirical models [7–16]. Cabrera et al. [7] determined the constitutive equations for the flow behavior of commercial Ti micro-alloyed steel. They conducted uniaxial hot compression tests over a wide range of strain rates (10^{-4}–$10\,s^{-1}$) and temperatures (1123–1423 K) and showed the inadequacy of the classical constitutive equations in taking the grain size into account. Chakravarty et al. [8] studied the characteristics of hot deformation of β-quenched Zr–2.5Nb–0.5Cu in the temperature range 650–1050 °C and in the strain rate range 0.001–100 s^{-1} using hot compression testing with the approach of processing maps and their interpretation through the Dynamic Materials Model. Cingara et al. [9] developed the constitutive equation relating peak stress, strain rate and temperature for hot working of 301, 304 and 317 steels using sinh equations. Laasraoui and Jonas [10] formulated the constitutive equations pertaining to idealized isothermal conditions for flow behavior of steels during deformation in the roll gap. Maheshwari et al. [11] used a modified Johnson–Cook (JC) material model to develop constitutive equations for hot deformation behavior of Al-2024 alloy. This empirical method depends on regression analysis to find the constants. The quantitative assessment of these models yields a wide range of errors which can go up to about 60% for a range of strain rates from (0.0001–100 s^{-1}). Many of the mechanisms of regression analysis do not describe the complex relationships of the various factors of flow stress with sufficient accuracy, because the effecting factors (strain, strain rate and temperature) of flow stress presents highly complicated non-linear interaction relationships during hot deformation. It is difficult to deal with the dispersed data through the regression method and also when a new experimental data is added, the regression constants need to be recalculated and moreover the regression method consumes a significantly longer time during computation. The research conducted by Guo and Sha [12], Malinov et al. [13] and Sun et al. [14] have mentioned the drawbacks concerning the development of constitutive relationship using conventional methods.

Recently artificial neural networks (ANN) have been applied for describing the hot deformation processes. The neural networks are a relatively new artificial intelligence technique that emulates the behavior of biological neural systems in digital software or hardware and this approach need not to have a well-defined process for algorithmically converting an input to an output. A significant advantage of the ANN approach is that one does not need to have a well-defined process for algorithmically converting an input to an output. Rather, it needs only a collection of representative examples of the desired mapping. The ANN then adapts itself to reproduce the desired output when presented with training sample input. Owing to their inherently high parallelism, ANN is ideally suited for the problem of estimating the flow stress from the available experimental data. ANN is the novel way to study the high temperature deformation behavior and some efforts have been made to the applications of ANN in some alloys. This model has good generalization performance without needing explicit mathematical and physical knowledge of deformation mechanism. The understanding of flow stress behavior in DSA regime becomes easier by using ANN modeling compared to modeling by constitutive equations.

Li et al. [15] established the predicting model for the calculation of flow stress of Ti-15–3 alloy based on the ANN method. Reddy

Table 2
Temperatures and strain rates in DSA region of austenitic stainless steel 316.

Temperatures (°C)	350	400	450	500	550	600	650
Strain rates (s^{-1})	10^{-4}	10^{-4} 10^{-3} 10^{-2}	10^{-4} 10^{-3} 10^{-2}	10^{-4} 10^{-3} 10^{-2}	10^{-4} 10^{-3} 10^{-2}	10^{-4} 10^{-3} 10^{-2}	10^{-4} 10^{-3} 10^{-2}