Prediction of hot deformation behavior of high phosphorus steel using artificial neural network

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Abstract
To predict the hot deformation behavior of high phosphorus steel, the hot compression experiments were performed with the help of thermo-mechanical simulator Gleeble® 3800 in the temperatures ranging from 750 ºC to 1050 ºC and strain rates of 0.001 s⁻¹, 0.01 s⁻¹, 0.1 s⁻¹, 0.5 s⁻¹, 1.0 s⁻¹ and 10 s⁻¹. The experimental stress-strain data are employed to develop artificial neural network (ANN) model and their predictability. Using different combination of temperature, strain and strain rate as a input parameter and obtained experimental stress as a target, a multi-layer ANN model based on feed-forward back-propagation algorithm is trained, to predict the flow stress for a given processing condition. The relative error between predicted and experimental stress are in the range of ±3.5%, whereas the correlation coefficient (R²) of training and testing data are 0.99986 and 0.99999 respectively. This shows that a well-trained ANN model has excellent capability to predict the hot deformation behavior of materials. Comparative study shows quite good agreement of predicted and experimental values.

1. Introduction
Iron shows an excellent corrosion resistance property due to presence of phosphorus, the example of these are Delhi iron pillar and iron beam in Konark and Puri. This provides the base to develop phosphoric irons for different engineering process and application [1]. In steel, phosphorus creates brittleness by segregation at grain boundary. Adding a small amount of carbon (0.01 to 0.05 wt%) in phosphoric irons followed by heat treatment process at high temperature removes phosphorus away from grain boundaries, results improved ductility and toughness [2-3]. In chloride-containing concrete reinforcement application, phosphoric steel does not show any signs of cracking due to stress corrosion, as in high strengthened and prestressed steels. Also in highly salty marine environment, phosphoric steel imparts better corrosion resistance properties [4]. To delineate formability and mechanical property at higher temperature for different industrial purpose, the knowledge of hot deformation behavior of material is necessary. Flow stress is the basic performance element to describe the hot deformation behavior of materials [5]. During hot deformation process, the effect of strain rate and temperature should be studied precisely to determine the microstructural evolution of materials [6-7]. For a wide range of strain rates and temperatures, the hot deformation behaviors of certain materials and the response of various parameters on the flow stress are highly nonlinear in nature, and this affects the accuracy of prediction. Constitutive equations are used to describe the dynamic restoration phenomena for a given conditions of temperatures and strain rates [8]. Artificial neural networks (ANN) are more suitable to solve the problems as compare to constitutive equations, since ANN does not need any mathematical model. The important characteristic of ANN is that it
learns from the available set of data and recognizes patterns without any prior assumptions, and gives better results. Therefore, ANN is easiest approach to solve any complex material modeling [9]. Zhao et al. investigated the deformation characteristics of a Ti600 titanium alloy using thermo-mechanical simulator Gleeble 1500D in temperatures ranging from 760 °C to 920 °C and strain rates ranges from 0.01 s⁻¹ to 10 s⁻¹. From microstructural studies, it was observed that at different deformation temperatures dynamic recrystallized (DRX) grains shows different shapes, and also reported that more severe distortion around the dynamic recrystallized grains were at lower temperatures as compared to higher temperatures. Constitutive equations and ANN are used to predict the flow stress [10]. Sabokpa et al. performed isothermal hot compression tests on cast AZ81 magnesium alloy in the temperatures ranging from 250 °C to 400 °C with strain rates of 0.0001 s⁻¹ to 0.01 s⁻¹ and predicted flow stress using constitutive equation and ANN, and found ANN more efficient [11]. Liu et al. performed isothermal hot compression test using Gleeble 3500 on 300M steel in the strain rates ranging from 0.1 s⁻¹ to 25.0 s⁻¹ and reported that the neural network model is better to predict flow stress as compared to regression method [12]. Li et al. conducted hot compression tests on modified 2.25Cr-1Mo steel in the temperatures ranging from 1173 K to 1473 K and strain rates from 0.01 s⁻¹ to 10 s⁻¹, and observed that the well-trained ANN model predicts the deformation behavior more accurately [13]. Bahrami et al. investigated mechanical properties of dual phase (DP) steels using neural network model in the temperatures ranging from 150 °C to 450 °C. Results show that ANN has a great potential to predict the mechanical behavior of dual phase steel [14]. Although there are many literatures that predict the hot deformation behavior of different material using constitutive equations and ANN approach. But there is no study available that predict the hot deformation behavior of high phosphorus steel in the wide temperature and strain rates using artificial neural network (ANN). Hence, there is need to investigate the hot deformation behavior of high phosphorus steel, and verify the predicted flow stress values with experimental flow stress using ANN model. In this work, isothermal hot deformation tests were performed with the help of thermo-mechanical simulator Gleeble® 3800 in temperatures ranging from 750 °C to 1050 °C and strain rates of 0.001 s⁻¹, 0.01 s⁻¹, 0.1 s⁻¹, 0.5 s⁻¹, 1.0 s⁻¹ and 10 s⁻¹ up to a true strain 0.7. Flow curves are drawn with experimental data and compared with predicted data obtained using ANN.

2. Experimental methods

2.1. Material and methods

A small piece of 30 mm x 40 mm x 30 mm was cut from prepared casting. Obtained small pieces were hot forged at 950 °C to prepare 12 mm diameter rod, which was further utilize to prepare hot compression test specimens. The chemical composition of high phosphorus steel is given in table 1.

| Element | Mn | P  | C  | Si | Cr | Ni | Cu | Al | W  | Fe  |
|---------|----|----|----|----|----|----|----|----|----|-----|
| Composition | 0.2 | 0.13 | 0.05 | 0.26 | 0.13 | 0.07 | 0.02 | 0.003 | 0.02 | 99.12 |

2.2. Hot compression test

Using Gleeble® 3800 thermo-mechanical simulator, hot compression tests were performed on specimens having dimension of 10 mm diameter and 15 mm length at constant strain rates ranging from 0.001 s⁻¹ to 10 s⁻¹. Specimens were heated with the heating rate of 5 °Cs⁻¹ up to austenitization temperature of 1050 °C followed by cooling at cooling rate of 1 °Cs⁻¹ up to the deformation temperatures range of 750 °C to 1050 °C with increment of 50 °C. To reduce the friction between ISO T-anvils and specimens, graphite foil and lubricant (nickel based) are used. To control the temperature during the process, K-type thermocouple was spot welded at the middle portion of the specimens. All specimens were deformed up to a true strain of 0.7 followed by in-situ water quenching to preserve microstructure of the deformed specimens.
2.3 Modeling with artificial neural network
To describe material behavior at different processing conditions, a single artificial neural network (ANN) is sufficient as compared to any other conventional computational tool. Artificial neural network contains number of neurons, which interact each within the network, and adjust its weights that minimizes the error between output and actual values [15]. In present study, an ANN model based on feed-forward back propagation (BP) algorithm is developed using MATLAB R2014b toolbox, which describes the flow behavior of high phosphorus steel. The BP iterative gradient training algorithms is used during training of network, because it minimizes the mean square error between the predicted output and targeted output. Levenberg-Marquardt (L-M) as training function is used to solve various non-linear optimization problems in this study. Total 252 experimental input-output datasets were utilized in this model. Among this dataset about 80% of the data are used for training, 10% for testing, and remaining data are used for validation purpose. ANN consists of three layers input, output, and hidden layer as shown in figure 1.

Figure 1. Structure of artificial neural network
Deformation temperature, strain and strain rate are taken as input data, and flow stress as output data for training process. ‘Trainlm’ is taken as training function, and ‘tan sigmoid’ and ‘pure linear’ as transfer function for corresponding input and output layer. Based on minimum mean square root, the number of neurons in a hidden layer is decided 10 after number of trails. All data sets were normalized in the range of 0 to 1 using equation (1), because mixed experimental data will confuse the learning process.

\[
X' = 0.1 + 0.8 \times \left( \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \right)
\]

(1)

where \(X\) is the original value, and \(X'\) is normalized value of quantity \(X\). \(X_{\text{max}}\) and \(X_{\text{min}}\) are maximum and minimum values of \(X\), respectively. Further, the predictability of ANN model is expressed in the form of relative error and correlation coefficient \((R^2)\). The relative errors (RE) are calculated using equation (2) [16].

\[
RE = \left( \frac{E_i - P_i}{E_i} \right) \times 100\%
\]

(2)

where \(P_i\) and \(E_i\) are predicted and experimental values for a given conditions.
The correlation coefficient ($R^2$) is used for performance evaluation of ANN models, and is expressed in equation (3).

$$R^2 = \frac{\sum_{i=1}^{N} (E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N} (E_i - \bar{E})^2 \sum_{i=1}^{N} (P_i - \bar{P})^2}}$$  \hspace{1cm} (3)$$

where $P_i$ is the predicted sample value using ANN model, $E_i$ is the sample of experimental value, $\bar{P}$ and $\bar{E}$ are the mean values of $P$ and $E$, respectively, and $N$ is the number of stress-strain samples. The performance of model improves as the value of $R^2$ approaches to 1 [17].

3. Results and discussion

3.1 Flow behavior

Experimental data obtained from hot compression tests of specimens of high phosphorus steel for different processing condition were utilized, to draw the flow curves. The sample flow curves of deformed samples for strain rate 0.001 s$^{-1}$, 0.1 s$^{-1}$ and 10 s$^{-1}$ at different deformation temperatures are shown in figure 2. From these flow curves, it is clear that for a specific strain rate the flow stress decreases with the increasing temperature, and for a constant temperature the flow stress decreases with decreasing strain rate (figure 2). True stress-strain curves at strain rates of 0.001 s$^{-1}$ for deformation temperatures ranging from 750 °C-900 °C, at strain rates of 0.1 s$^{-1}$ and temperatures 950 °C-1000 °C, and for strain rate of 10 s$^{-1}$ and deformation temperature of 1050 °C initially shows the strain hardening followed by softening. The peak in the flow stress curves shows the onset of DRX process. With increase in strain rate or decrease in deformation temperature, the stress peaks are shifted towards the higher strain, because at higher strain rates and/or lower deformation temperatures the rate of work hardening increases as compared to the rate of softening due to DRX. In general, with the reduction in deformation temperature or increase in strain rate, the values of flow stress gradually increase for entire testing strain. The flow curves at low strain rate and higher temperatures (0.001 s$^{-1}$ at deformation temperatures 950 °C-1050 °C) show multi peaks due to multiple dynamic recrystallizations (MDRX), and new grains are developed from old grains figure 2a.
Figure 2. True stress vs. true strain curves of high phosphorus steel obtained from hot compression at different deformation temperature and strain rates of (a) 0.001 s\(^{-1}\), (b) 0.1 s\(^{-1}\), and (c) 10 s\(^{-1}\).

3.2 Evaluation of ANN performance

For wide range of deformation temperatures and strain rates, ANN shows a good correlation coefficient for BP algorithm and predicts flow stress accurately and efficiently as shown in figure 3. The value of predicted flow stress using ANN in training and testing were compared with experimental flow stress, and observed the corresponding relative errors in the range of ±3.5%.

Figure 3. Correlation between the predicted and experimental flow stress for the (a) training data, and (b) testing data.

For deformation temperatures ranging from 750 °C to 1050 °C and strain rates of 0.001 s\(^{-1}\), 0.1 s\(^{-1}\), and 10 s\(^{-1}\), the variations between experimental flow stress and predicted values of flow stress from ANN are represented in figure 4. It is observed from results that predicted flow curves drawn using ANN shows a close agreement with experimental flow curves.
Figure 4. Comparisons between the experimental (colored lines) and predicted (dotted points) flow curves with the help of ANN at different deformation temperatures for strain rates (a) 0.001 s$^{-1}$, (b) 0.1 s$^{-1}$, and (c) 10 s$^{-1}$, of high phosphorus steel.

4. Conclusions

The hot deformation behavior of high phosphorus steel is studied in the temperatures ranging from 750 °C to 1050 °C and strain rates ranges from 0.001 s$^{-1}$-10 s$^{-1}$. The following conclusions are drawn from this work.

1. The flow stresses value of high phosphorus steel increases with decrease in deformation temperature or increase in strain rates. This is due to increase in work hardening rate as compared to the softening rate due to DRX.
2. The relative error between predicted stress values and experimental stress are the range of ±3.5%, which shows an acceptable range of data.
3. The correlation coefficient ($R^2$) of training and testing data are 0.99986 and 0.99999, respectively. This shows that a well-trained ANN model has excellent capability to predict the hot deformation behaviour of materials.
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