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Neural Network Prediction of Warm Deformation Flow Curves in Ferrite+ Cementite Region

M. Rakhshkhorshid [1] , H. Rastegari [2*]

Department of Mechanical and Materials Engineering, Birjand University of Technology, South Khorasan 97198-66981, Iran

Abstract

Many efforts have been made to model the the hot deformation (dynamic recrystallization) flow curves of different materials. Phenomenological constitutive models, physical-based constitutive models and artificial neural network (ANN) models are the main methods used for this purpose. However, there is no report on the modeling of warm deformation (dynamic spheroidization) flow curves of any kind of steels. In this work, a neural network with feed forward topology and Bayesian regularization training algorithm was used to predict the warm deformation flow curves of a eutectoid steel. The experimental data was provided by sampling the dynamic spheroidization flow curves of the tested steel obtained from warm compression tests conducted over a temperature range of 620-770 °C with different strain rates in the range of 0.01-10 s^{-1}. To develop the neural network model, the overal data was divided into three categries of training, validation and testing. The scatter diagrams together with the root mean square error (RMSE) criterion were used to evaluate the prediction performance of the developed model. The low calculated RMSE value of 4.15 MPa for the overall data showed the robustness of the developed ANN model in predicting the warm deformation flow curves of the tested steel. The results can be further used in the mathematical simulation of warm metal forming processes.

Keywords: Warm deformation; Flow stress; Artificial neural network model; Dynamic spheroidization.

1. Introduction

Deformation at elevated temperatures plays an important role in manufacturing materials with the required mechanical properties. For this reason, deformation parameters such as temperature, strain rate and the applied strain must be controlled carefully by mathematical simulations. In this regard, modeling of flow curves extracted from metal-forming experiments such as compression and torsion by constitutive equations is a necessary stage to describe the material flow behavior. Hence, considerable researches have been conductedto model the flow stress of metals and alloys and different constitutive equations have been proposed to model the flow stress of different materials [1-4).

Based on the literature, the constitutive models can be divided into three categories including phenomenological constitutive models, physical-based constitutive models, and artificial neural network (ANN) models [5)]. As it is known, the flow curves of the materials at elevated temperatures are nonlinear and work hardening and dynamic softening behaviors often occur in these flow curves. Therefore, it is very hard to show the relationship between deformation parameters and flow stress via an accurate mathematical model. However, this problem can be effectively solved through establishing ANN models. The ANN-based model needs neither mathematical model nor deformation mechanism; it is able to directly learn the rules of change between the input variables and the output variables from testing data, and store these rules into weight and threshold values of the network through its own good ability of nonlinear mapping. Therefore, mathematical formulas are not required to intuitively express the relationship between flow stress and parameters such as strain, temperature and strain rate. Furthermore, ANN has a wide applicability. It can effectively predict the flow stress in the whole scope of working deformation [6-10)].

In the present research, the capability of ANN was evaluated for warm deformation flow curves of some eutectoid steel. According to the authors' knowledge, there is no report concerning the modeling of the flow curves of eutectoid steel at warm deformation conditions by ANN. Thus, the aim of the present study was

* *Corresponding Author*
Email: rastegary@birjandut.ac.ir
Address: Department of Mechanical and Materials Engineering, Birjand University of Technology, South Khorasan, P.O. Box: 97198-66981, Iran
1. Assistant Professor
2. Assistant Professor

to evaluate the ability of ANN models in predicting the flow curves during the compression test.

2. The Experimental Data

The material used in this study was a 10 mm diameter hot-rolled eutectoid steel rod. Chemical composition of the plain eutectoid steel is (in wt. %) 0.82 C, 0.18 Si, 0.66 Mn, 0.012 P, 0.005 S and 0.003 N (SWRH82B-DLP according to JIS G3506 standard). The specimens with the height of 10 mm and the diameter of 8 mm were prepared. In order to minimize friction and barreling effects due to the existence of friction between the anvils and the specimen surface, graphite foil was employed as a lubricant. Single-hit warm compression tests were performed by employing a Gleeble1500 thermomechanical simulator. The specimens were reheated at the rate of 20 °C/s to the deformation temperature of 620, 670, 720 and 770 °C, held for 15 s and then compressed to a true strain of 0.5 at a constant true strain rate of 0.01, 0.1, 1 and 10 s^{-1}. Smoothed true stress- true strain curves obtained at different temperatures and strain rates are depicted in Fig. 1. It was obvious that the onset of dynamic spheroidization of cementite lamella during warm compression, due to the softening effect, could be identified by a single peak stress followed by a gradual fall.

The experimental stress-strain curves obtained at different deformation temperatures and strain rates [11)] were sampled for different strains in the range of 0.01 to 0.45 and the step size of 0.01. So, a database with the input variables of the deformation temperature, strain rate and strain, and the output variable of flow stress with 720 patterns was prepared. The provided data base was used to develop the neural network model. It is worth mentioning that, according to the deformation condition (Temperature and Strain rate) and metallographic observations (As shown in the previous research [11)], the main mechanism is dynamic spheroidization. Thus, the deformation mechanism remains constant with strain rate and temperature. It should be noted that the onset of dynamic spheroidization during compression, due to the softening effect, could be identified by a distinct peak in the stress-strain curve followed by flow softening (Fig. 1).

3. Bayesian Regularization Artificia Neural Network

In this section, a brief description about the Bayesian regularization artificial neural networks is provided. Then, the presented model is developed based on the training, validation and testing stages and explained with more details in the next parts.

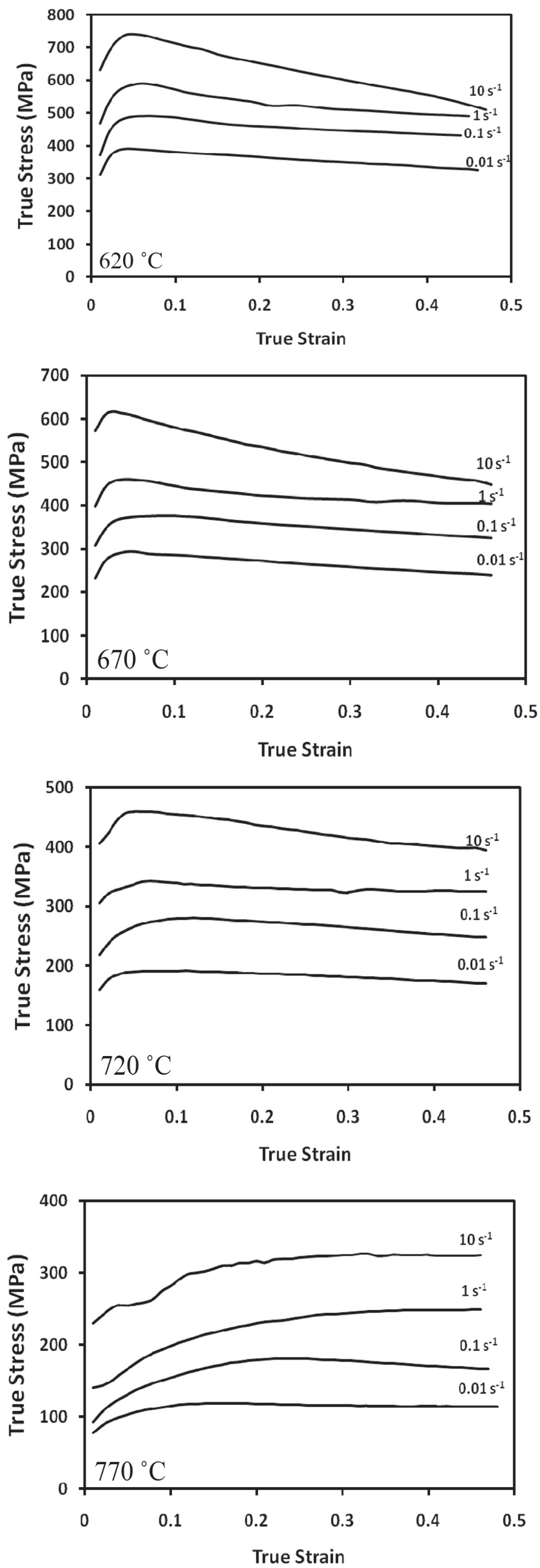

Fig. 1. Experimental flow curves of eutectoid steel at different warm deformation conditions [1)].

3.1. Architecture of the developed ANN model

In artificial neural networks, a network of highly interconnected processing elements can work together to solve a specific problem [12]. In this work, a feed forward neural network with feed forward topology and Bayesian regularization training algorithm was used to predict the warm deformation (dynamic spheroidization) flow curves of a eutectoid steel. This neural network could approximate any function with a finite number of discontinuities. For designing these networks, one input layer, one or more hidden layers with sigmoid transfer functions, and one output layer with linear transfer function are often used [13]. The number of nodes in the input and output layers is equal to that of the input and output variables, respectively. The number of hidden layers and nodes could be obtained through trial and error during training and testing the network.

Here, a three-layer network with logistic sigmoid transfer function was designed to predict the warm deformation (dynamic spheroidization) flow curves of the tested steel. The flow stress of the tested steel at different deformations was a function of the variables of temperature, strain rate and strain. So, the architecture depicted in Fig. 2 was designed to develop the desired neural network model.

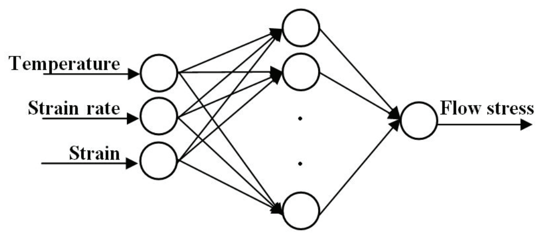

Fig. 2. The architecture designed in this research.

3.2. Neural network training, validation and testing

After the construction of the neural network structure, a training algorithm should be used to adjust the weights and biases of the network iteratively; this should be done in a way to minimize the network performance function. The common used performance function in these neural networks is Mean Square .

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(t_i - y_i\right)^2 \qquad \text{(Eq. 1)}$$

, where t_i and y_i are the target (actual) and predicted values of the ith pattern of the output variable y, respectively, and n is the number of data patterns used for training the network.

In this work, Bayesian Regularization was used for training the network. In the Bayesian regularization training algorithm, weights and biases are updated with Levenberg-Marquardt optimization algorithm and the network generalization can be improved by minimizing a combination of MSE and the mean square of the network weights. The weights are considered as random variables with Gaussian distribution [15].

To improve the generalization property of the proposed neural network model, the early stopping technique was used and the overall data was randomly divided into three subsets of training, validation and testing. In this technique, training process should be stopped when the error for the validation set starts to increase. The error value for tests shows if the over fitting has occurred or not [16]. As mentioned before, the prepared data base was composed of 720 patterns, from which 432 randomly selected patterns were used for training the network. The remaining data were divided equally into two subsets to validate and test the trained network.

The neural networks are very sensitive to the nodes in hidden layers. The small number of those nodes can result in low fitting and the high number of over fitting. Here, to assess the effectiveness of the network, the scatter diagrams together with the root mean square error (RMSE) criterion were used:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(t_i - y_i\right)^2} \qquad \text{(Eq. 2)}$$

, where t_i is the target output, y_i is the model output and n is the number of data patterns. After some trial an error, it was found that the network with 40 nods in the hidden layer had the least error for the test data and increasing the number of these nodes did not improve the network results for training data.

4. Results and Discussion

The results of the developed Bayesian regularization neural network model for training, validating and testing the overall data patterns are presented in Fig. 3 in the form of scatter diagrams. As can be seen, there was an excellent agreement (with the correlation coefficient value of R = 0.9996 for the overall data) between the predicted and measured flow stresses.

Furthermore, the low RMSE values of 3.70, 4.06, 5.36 and 4.15 Mpa, which were obtained for training, validating and testing the overall data, respectively, evidencedthe excellent agreement. A comparison between the experimental and modeled flow curves (using the developed neural network) at different warm deformation conditions is presented in Fig. 4.

As shown, the flow curves of the tested steel at different warm deformation conditions could be followed smoothly by the neural network. Also, it could be observed that both hardening and softening behavior of the flow curves can be modeled effectively. The overall results showed the high and effective performance of the developed neural network model for the prediction of dynamic spheroidization flow curves of the tested eutectoid steel.

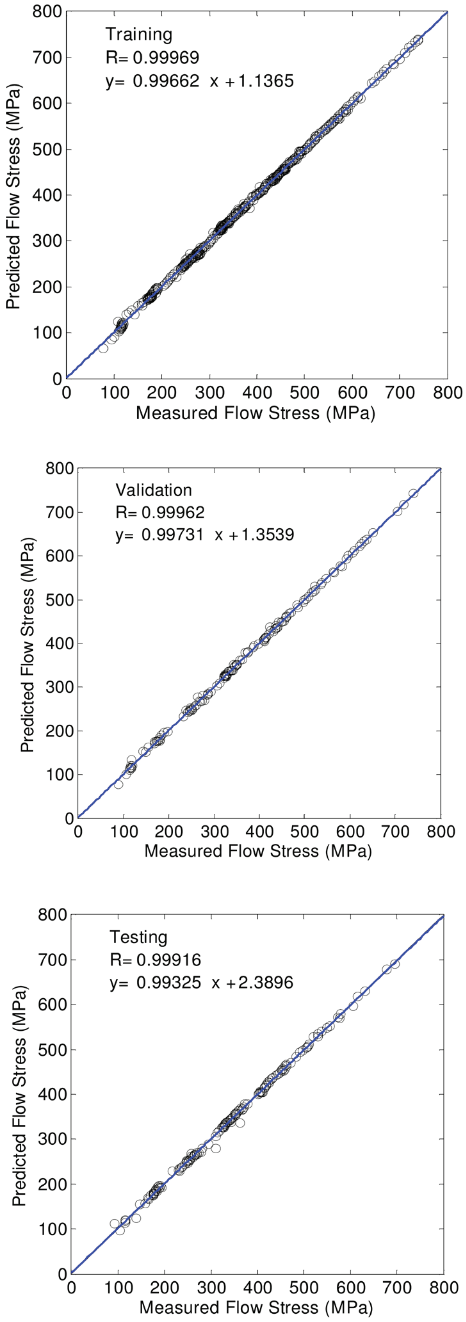

Fig. 3. The results of the developed Bayesian regularization neural network model for training, validating and testing the overall data patterns.

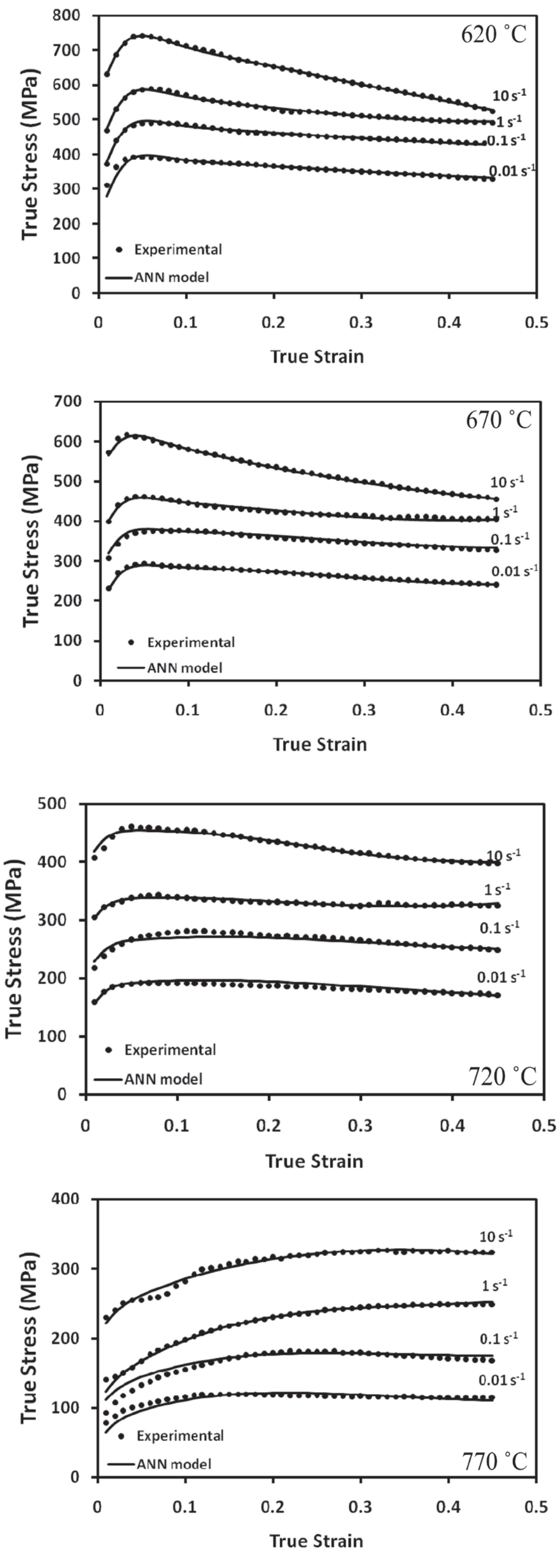

Fig. 4. The comparison between the experimental and modeled flow curves (using the developed Bayesian regularization neural network) at different tested warm deformation conditions.

5. Conclusions

In this research, the warm deformation flow stress of eutectoid steel was predicted using a Bayesian regularization neural network. The flow curves obtained from single hit compression testing at different warm deformation conditions were sampled. Consequently, a database with the input variables of deformation temperature, strain rate and strain, and the output variable of flow stress was obtained. Accordingly, the Bayesian regularization neural network model was developed to model the hot deformation flow curves of the tested steel. The low RMSE values of 3.70, 4.06, 5.36 and 4.15 Mpa, which were obtained respectively for training, validating and testing and the overall data, respectively, showed the robustness of the developed ANN model in predicting the warm deformation flow curves of the tested steel. In addition, it was found that the dynamic sphearoidization mechanism during warm deformation of eutectoid steel could be modeled by the developed ANN model.

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