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Isothermal Forging of Ti-6Al-4V Alloy - Flow Stress Evaluation and Optimization

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ABSTRACT

Narrow-forging-temperature range makes titanium alloys tough to forge. In this paper hot compression experiments on Ti-6Al-4V alloy specimens are conducted using Thermo mechanical Simulator Gleeble-3500. These objectives of the test were to obtain flow stress data under varying conditions of strain, strain rate and temperature. Furthermore, artificial neural network (ANN) was used for studying high temperature flow characteristics for Ti-6Al-4V alloy in terms of stress–strain curves. A predicting model was also established for the calculation of flow stress using ANN. Results show that the neural network can correctly reproduce the flow stress in the sampled data and can also predict the non-sampled data very well. These studies are significant for determining the hot-forging processing parameters of Ti-6Al-4V alloy.

Keywords: Isothermal Forging, Flow Stress, Thermo Mechanical Simulation, ANN.

I. INTRODUCTION

Today in this world of technological advancement isothermal forging is competing with the other more classical technologies for closed die forging. The basic principle consists of a plastic forming process with die and work piece temperatures identical or very similar. Isothermal forging represents a possible alternative to produce near net and net shape forgings. With this method it is possible to produce functional surfaces to finished tolerance. It is more advantageous than conventional forging process especially in terms of material and machining cost reduction. Material cost as in the case of components made of Ti-alloy with complex shapes, it is possible to reach savings up to 40-45%. It must also be said that for some components it is possible to finish forge in one step after having performed with different equipment. Machining costs are also generally reduced and depending on complexity and final tolerances, the savings can reach up to 30%. The most important resulting advantage is the possibility to produce forgings with very thin sections [1]. Artificial neural network (ANN) is one of the most researched and used technology in last two decades by industries and technocrats. It is a revolutionary tool in the world of soft computing related with realistic work. The back propagation network is probably the most well-known and widely used among all the current types of neural network systems available. The back propagation network is multilayer feed forward network with a different transfer function in the artificial neuron and a more powerful learning rule. The learning rule is known as back propagation, which is a type of gradient decent technique with backward error (gradient) propagation. Back-propagation neural network (BPNN) seems to be potentially useful tool for predicting and comparing the flow stress behaviour of titanium alloys experimentally forged with isothermal forging.

There also many researchers who have applied the Neural network method and neural fuzzy methodology in the various field of engineering and Technology. Very few researchers have applied the techniques of ANN to study the forging behaviour of titanium alloy and in other forging application. Hashmi et al. [2] developed a model based on fuzzy logic for selecting cutting speed in single point turning operations. In a similar vein, Arghavani et al. [3] applied a fuzzy logic approach to the selection of gaskets, for their sealing performance, based on system requirements. Guo and Sha [4] developed an artificial neural network (ANN) model for the analysis and simulation of the correlation between processing parameters and properties of managing steels and it is believed that the model can be used as a guide for practical optimization of alloy composition and processing parameters for managing steels. Miaoquan [5] developed a fuzzy neural network model to correlate the relationship between the grain size of forged materials and the process parameters of the forging process. Tang and Wang [6] developed an adaptive fuzzy control system to reduce the non-linear cutting behaviour of a CNC turning machine. Kuo [7] used the fuzzy theory to improve the neural network learning rate in the fault diagnosis of a marine propulsion shaft system.

The present investigation is directed towards the development of more comprehensive artificial model for flow stress prediction of titanium alloy Ti-6Al-4V. Neural network have been studied in the recent years in the hope of achieving humanlike performance in the various field of engineering. Neural networks are effective tools which can recognise similar patterns by training a network with particular pattern of data. Their parallelism, trainability and speed make the neural network fault tolerant as well as fast and efficient for handling large amount of data [8]. In this work an attempt have been made to develop a neural network model to predict the flow stress of Ti-6Al-4V alloy and to analyse the behaviour of alloy during isothermal forging in temperature range from 875-1025oC at various strain rates from 0.001s-1 to 10s-1. Further the result obtained from neuro-fuzzy model is compared with the neural network model.

II. METHODS AND MATERIAL

In order to artificial intelligence model to predict the flow stress behaviour of Ti-6Al-4V alloy, sample data sets are necessary for training, testing and validation. By taking into consideration the properties of Ti-6Al-4V alloy, temperature, strain, strain rate as the input process parameters, while flow stress was taken as the output parameter or target value as in neural network for modelling. Prior to the isothermal forging the specimens were prepared with a diameter of 10 mm and a height of 15 mm by a diamond cutter (Low speed saw, Buehler make) shown in Figs. 1, 2 and 3.

Figure 1: Low speed saw, a diamond cutter (Buelher make, USA).

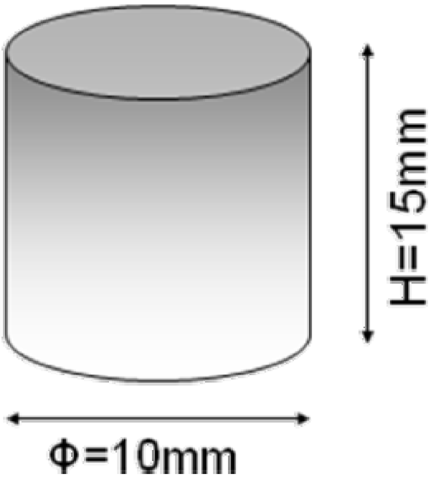


Figure 2: Sample prepared; D= 10 and H=15 mm

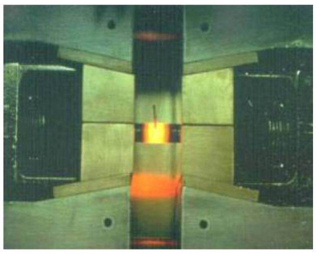



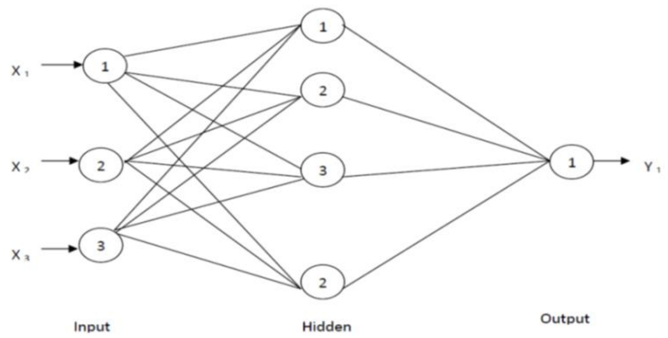
Figure 3: Thermo mechanical simulator (Gleeble-3500) for isothermal forging of the samples

III. RESULTS AND DISCUSSION

88 sets of data were generated by varying the temperature, strain rate and strain. The variations of these parameters are as follows:

• Temperature: From 875 to 1025^{o}C

• Strain: From 0.1 to 0.6 at the interval of 0.1.
• Strain Rate: From 0.001 to 10.



X1= Temperatures in ^{o}c X2= Strain X3= strain rate in s^{-1} Y1= Flow stress	Number of hidden layer=1 Number of neurons in hidden layer=21 Number of training iteration= 750 Learning rate= 0.7 Momentum factor= 0.4

Figure 4: Three layer back-propagation network architecture

For each temperature at different strain and strain rate the flow stress values are measured. The specified ranges of input parameters for the experimentations were selected based on the known industrial practice.

Out of the total data generated from the experiments, 9 sets of data were selected randomly for testing the developed model and another 9 sets for validation of the developed network model. The remaining 70 sets of data were used for training the proposed network model.

3.1 Development of neural network model

The learning algorithm selected for training the network is back-propagation algorithm. A C^{++} source code was compiled for developing the back-propagation neural network (BPNN) model. The developed model was trained until minimum error limit as desired was reached. The connection weights were stored in a text file and subsequently used for prediction of output parameters. The architecture of the network obtained can be seen in Fig.4. A sample set of data prepared for training the network is shown in Table 1. After the successful training of the network, the performance of the network was tested with the test data sets, which comprised of 9 sets of data randomly selected from those not included in training. The test data set is shown in Table 2. The response of the network was accessed by comparing the predicted values of the network with the experimental values to determine the predictive capability of the network. The network predicts the best possible value and minimum possible error as desired by authors when the selected input parameters are within limit as set by the user based on the obtained experimental result. The generalisation capability of the network has been validated with a set of 9 data, which has not included in the training and testing of the network.

Table.1: Sample data set for training the network model

Sl. No.	Temperature	Strain	Strain rate	Output
1	925	0.01	0.6	8.4077
2	1025	1	0.4	46.3148
3	925	0.1	0.5	62.908
4	875	0.1	0.2	168.502
5	875	0.01	0.6	51.097
6	975	0.01	0.1	22.806
7	925	0.1	0.6	29.03
8	975	10	0.6	97.3088
9	925	0.01	0.1	43.23
10	875	1	0.2	231.55
11	1025	0.1	0.3	37.581
12	875	0.01	0.1	114.1
13	975	0.01	0.3	17.9614
14	925	10	0.6	105.614
15	1025	10	0.1	71.5356
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67	975	0.01	0.6	3.192
68	925	1	0.1	125.312
69	1025	10	0.6	52.4644
70	875	0.01	0.5	59.917

Table 2: Sample data set used for testing the network model

Sl. No	Temperature	Strain	Strain Rate	Output
1	1025	10	0.5	72.6026
2	1025	1	0.2	47.5798
3	975	0.01	0.4	15.4082
4	925	10	0.3	187.818
5	925	0.1	0.2	86.6382
6	875	0.1	0.2	168.502
7	1025	1	0.4	46.3148
8	925	0.01	0.1	43.23
9	875	1	0.3	212.462

Table 3: Comparison of actual and predicted flow stress of Ti-6Al-4V alloy

Sl. No.	Temperature	Strain rate	Strain	Actual Output	Predicted (ANN)	%Error
1	1025	10	0.5	72.6026	76.3	1.37
2	1025	1	0.2	47.5798	46.23	2.8
3	975	0.01	0.4	15.4082	19.8	22.1
4	925	10	0.3	187.818	209.5	10.3
5	925	0.1	0.2	86.6382	88.8	2.4
6	875	0.1	0.2	168.502	161.2	4.3
7	1025	1	0.4	46.3148	52.32	11.4
8	925	0.01	0.1	43.23	45.32	4.6
9	875	1	0.3	212.462	209	1.6

IV. CONCLUSION

Hot deformation parameters have significant effects on the flow stress of Ti-6Al-4V alloy. The flow stress decreases with temperature and increases with strain rate. The deformation degree for the maximum flow stress shifts towards higher strain values with increasing temperature and increasing strain rate. A neural network predicting the behavior of Ti-6Al-4V alloy under isothermal forging condition, and analyzing the relationship between temperature, strain rate and strain with the flow stress was developed. The predicted values of output i.e. Flow stress of both the model are in good agreement with the experimental values.

V. ACKNOWLEDGEMENT

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