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Prediction of Flow Stress of Ti-6Al-4V Alloy Forging: An Artificial Neural Network and Neuro-fuzzy Based Approach

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Abstract

In this paper, an adaptive model for Ti-6Al-4V alloy of titanium to predict the flow stress of it under isothermal forging condition has been established with the help of artificial neural network (ANN) and fuzzy neural network (FNN) and to analyse the properties of Ti-6Al-4V. Datas for the model were generated following standard experimental procedure in the Research and Development centre for Iron and Steel, SAIL, Ranchi, India. Process parameters such as Temperature, strain rate, strain were varied in limit. The data thus collected were used in developing these models. The predicted output of flow stresses by neural network and neuro-fuzzy based models have been found to be in good agreement with experimental values. Furthermore, it has been observed from the result that the predicted value from neuro-fuzzy models is more accurate than those predicted from the neural network model.

Keywords: Isothermal forging, flow stress, Neuro-fuzzy model, neural network model

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 –

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45%. It must also be said that for some components it is possible to finish forge in one step after having preformed 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 (Altan, et al., 1973)'.

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. Li Ping, Xue Kemin, Lu Yan and Tan Jianrong have done the flow stress evolution with the use of ANN for Ti-15-3 forge alloy (Ping et al., 2004)'. A user friendly system for selection of process parameters for Electro Discharge machine was done using this technique for electrically conductive materials (Yilmaz et. al., 2006)'. (Hashmi et. al., 2006)' developed a model based on fuzzy logic for selecting cutting speed in single-point turning operations. In a similar (Arghavani et. al., 2001)' applied a fuzzy logic approach to the selection of gaskets, for their sealing performance, based on system requirements. (Guo et. al., 2004)' developed an artificial neural network (ANN) model for the analysis and simulation of the correlation between processing parameters and properties of maraging steels and it is believed that the model can be used as a guide for practical optimization of alloy composition and processing parameters for maraging steels. (Malinov et. al., 2001)' established an ANN model which can be used for the prediction of properties of titanium alloys at different temperatures as functions of processing parameters and heat treatment cycle and can also be used for the optimization of processing and heat treatment parameters. Miaoquan 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 developed an adaptive fuzzy control system to reduce the non-linear cutting behaviour of a CNC turning machine. Kuo used the fuzzy theory to improve the neural network learning rate in the fault diagnosis of a marine propulsion shaft system (Kuo et. Al., 2000)'.

Neuro- fuzzy network system (FNN) which combines the element of both neural network and fuzzy methodology, work in a similar way to back-propagating neural network system. In neural network the model is not defined in prior but is obtained through a process of data training. The network progressively builds the input and output function by presenting couples of input and output data. For every input value network itself calculate the expected output value. The learning algorithm modifies the weights between neurons thus minimizes the error until as desired. Fuzzy expert system donot require the generation of rules for a fuzzy neural network model. The learning algorithm in neuro-fuzzy system modifies the analytical expression of the function so as to diminish the total error.In recent years neuro- fuzzy models have been applied in forging, machining, metallurgy, scheduling, inspection, planning and fault diagnosis.

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 and fuzzy models have been studied in the recent years in the hope of achieving humanlike performance in the various

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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 (Reddy et. al. 1996)'. The fuzzy based system attempt to match human behaviour in solving problems that cannot be formalised by the use of mathematical models. Fuzzy models require expert and decision maker who are well familiar with the process states and the input output relationship to generate the language or linguistic rules.

In this work an attempt have been made to develop a neural network model and an Neuro-fuzzy system to predict the flow stress of Ti-6Al-4V alloy and to analyse the behaviour of alloy during isothermal forging in temperature range from 875-1025^{0} C at various strain rates from 0.001s^{-1} to10s^{-1}. Further the result obtained from Neuro-fuzzy model is compared with the neural network model.

II. EXPERIMENTAL PROCEDURE

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, Buelher make) shown in fig. 1 & 2.

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

Fig.2: Sample prepared; D= 10 & H= 15 mm.

The experiment was performed with standard experimental procedures on a thermo-mechanical simulator (Gleeble-3500) to give a different true strain rate with strain. All the tests were carried out under isothermal conditions. The temperatures of the specimens were closely monitored with the fine thermocouple inserted into a 0.8 mm hole drilled at half the height of the specimen. The specimens were deformed to 60 % and the load-stroke data were recorded. The specimens were air-cooled, sectioned parallel to the compression axis and micro structural examination by image analysis system was done by following standard procedures. The flow stress values were obtained as a function of temperature, strain rate and strain.

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

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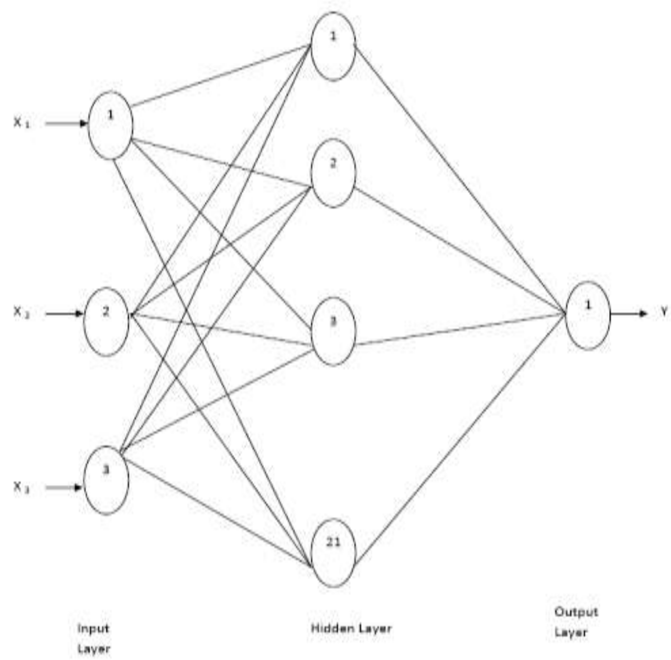
Temperature: From 875 to 1025^{o}C

Strain: From 0.1 to 0.6 at the interval of 0.1.

Strain Rate: From 0.001 to 10.

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. The three layer back propagation network is shown in fig. 3.



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

Fig.3: Three layer back-propagation network architecture

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.

III. 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 3. 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
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68	925	1	0.1	125.312

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Sl. No	Temp	Strain rate	Strain	Actual Output	Predicted by FNN	Error (%)	Predicted (BPNN)	Error (%)
1	1025	10	0.5	72.602	67.1	7.5	76.3	1.37
2	1025	1	0.2	47.579	42.5	10.6	46.23	2.8
3	975	0.01	0.4	15.408	17.8	11.2	19.8	22.1
4	925	10	0.3	187.81	214	12.2	209.5	10.3
5	925	0.1	0.2	86.638	86.8	0.018	88.8	2.4
6	875	0.1	0.2	168.50	159	5.6	161.2	4.3
7	1025	1	0.4	46.314	46.3	0	52.32	11.4
8	925	0.01	0.1	43.23	43	0.305	45.32	4.6
9	875	1	0.3	212.46	201.23	5.2	209	1.6

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 Predicted Results

The predicted result and their percentage error are given in the Table 3.

IV. DEVELOPMENT OF NEURO-FUZZY MODEL

The same sample data sets that were used for the back-propagation neural network model were used for the development of fuzzy neural network model. The input and output variables remain unchanged with regard to the neural network model. Designing and training of adaptive fuzzy model were performed using the MATLAB Fuzzy logic toolbox . The learning algorithm that is used for the system to learn from data is a hybrid model which is a combination of back-propagation and a least square method and the training stopping criterion was selected on the basis of error tolerance. When the training data was loaded, the adaptive fuzzy system automatically developed a sugeno type inference system (FIS) from input/output data for learning. The disjunction and defuzzification operated selected were prod (algebraic product) and wtaver (weighted average of the output distribution) respectively. The outputs of the various rules were aggregated according to a fuzzy "weighted average". In the learning process of the developed neuro-fuzzy model, all the membership function of the variables were assigned Gaussian type membership function of the parameters subspaces were determined by using grid means of the training set.

The fuzzy rules generated by the learning process are as follows:

Rule 1: IF (TEMPERATURE is in1mf1) and (STRAIN RATE is in2mf1) and (STRAIN is in3mf1) THEN (FLOW STRESS is out1mf1) (1).

Rule 2: IF (TEMPERATURE is in1mf2) and (STRAIN RATE is in2mf2) and (STRAIN is in3mf2) THEN (FLOW STRESS is out1mf2) (1).

Rule 1: IF (TEMPERATURE is in1mf3) and (STRAIN RATE is in2mf3) and (STRAIN is in3mf3) THEN (FLOW STRESS is out1mf3) (1).

Rule 63: IF (TEMPERATURE is in1mf63) and (STRAIN RATE is in2mf63) and (STRAIN is in3mf63) THEN (FLOW STRESS is out1mf63) (1).

Rule 64: IF (TEMPERATURE is in1mf64) and (STRAIN RATE is in2mf64) and (STRAIN is in3mf64) THEN (FLOW STRESS is out1mf64) (1).

A representation of the neuro-fuzzy model structure can be seen in fig.4.

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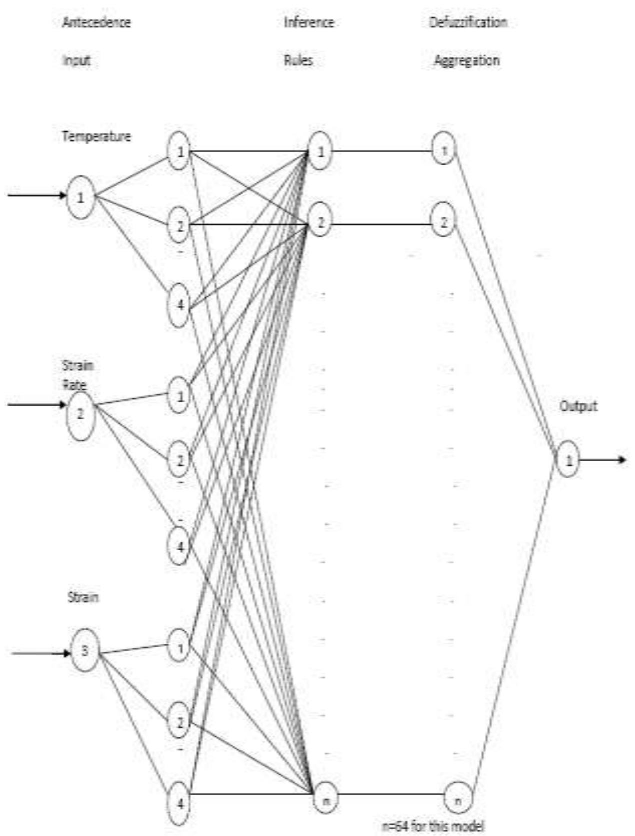

Fig. 4: Neuro-fuzzy model developed

The input layer receives the input values and transmits them to next layer without making changes. The membership function layer computes the matching degree between each single fuzzy condition (antecedents of the if-then rules) and each output. The rule layer computes the matching degree of the conjunctive fuzzy condition involving multi variables. The inferential layer propagates the matching degree of the rules to the inferred condition. The aggregation layer contains the normalisation code and the inferred conclusions are aggregated according to the fuzzy aggregation operator. The output layer finally defuzzifies the possibility distribution resulting from aggregation of the inferred conclusions, producing the numerical output, producing the numerical output at the exit of the system (Nagur et. al., 2006)'.

V. RESULT AND DISCUSSION

The fuzzy neural network model developed after the training was tested for the test data and was further used to predict the output i.e. Flow stress of the Ti-6Al-4V alloy.

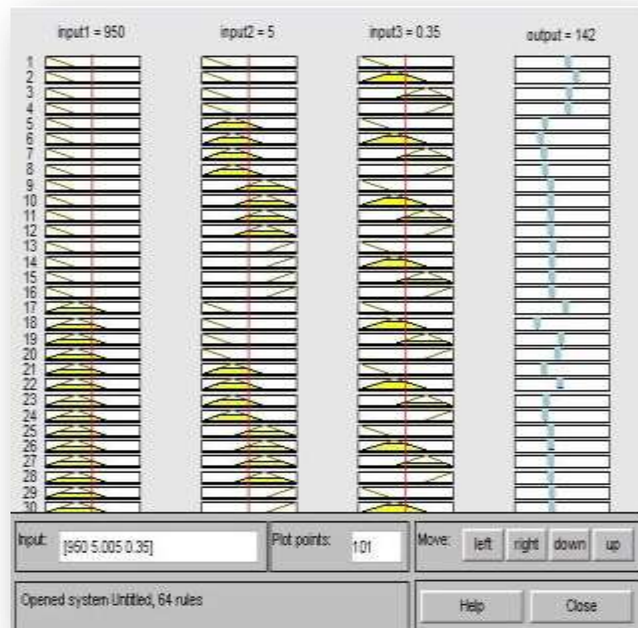

Fig. 5: Rule viewer of generated neuro-fuzzy model to predict flow stress of Ti-6Al-4V.

Where input 1 = Temperature; input 2 = strain rate; input 3 = strain; output = Flow stress in Mpa

FNN develops a rule viewer which is shown in fig.5 to predict the output values (Flow stress) from the trained fuzzy inference system. The rule viewer plots every part of each rule and shows how membership function influences the overall output. In the rule viewer a set of input attributes for alloy has been given and the rule viewer then gives the defuzzified output (predicted flow stress) corresponding to assigned input values of temperature, strain rate and strain. Similarly the output values for other inputs could also be predicted with the rule viewer when the input variables selected are within the best possible

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ranges of input process parameters.Figure4 represents the output surface generated by proposed neuro-fuzzy model. This surface graph is helpful in analysing the ranges input process parameters, temperature, strain rate, strain and the corresponding output parameter, flow stress.

The predicted result of neuro-fuzzy model were compared with the result of back- propagation neural network model. Table 3 shows the comparison of predicted flow stress values by the two separately developed model of FNN and BPNN. It can be clearly seen from the table that the maximum and minimum percentage of error obtained by neuro-fuzzy model is 12.2 and 0 whereas for artificial neural network is 22.1 and 1.37.Clearly, the neuro -fuzzy model can predict the behaviour of Ti-6Al-4V alloy more accurately than the neural network model because of high learning precision and generalisation. It has also be seen that training in neuro-fuzzy model takes less duration than Back-propagation neural network model. Compared to the ANN model both the number of iteration and number of trials required for training the network to achieve optimum training error are less in case of neuro-fuzzy model developed. Thus there was considerable amount of time saving in the development of neuro fuzzy model developed.

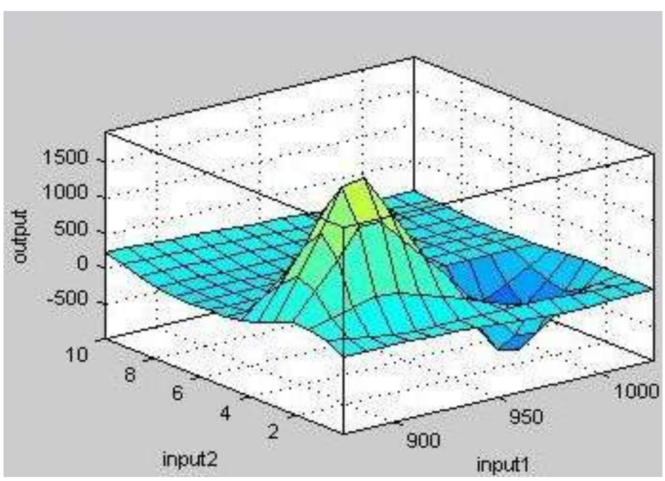

Fig. 6: Output surfaces generated by neuro-fuzzy model for temperature, strain rate and output**.**

Where input 1 = Temperature; input 2 = Strain rate; Output = Flow stress in Mpa

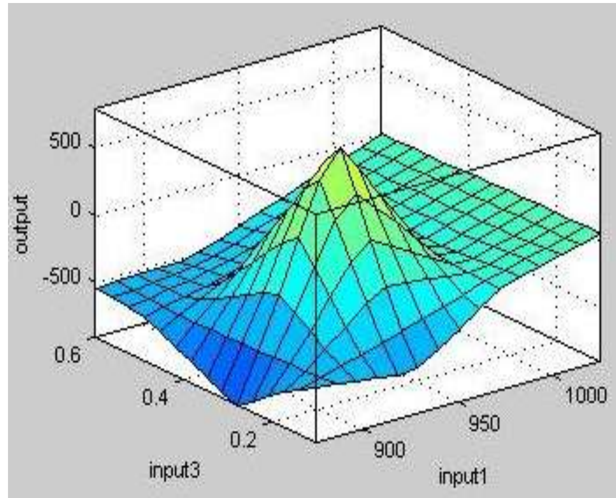

Fig. 7: Output surfaces generated by neuro-fuzzy model for temperature, strain and output

Where input 1 = Temperature; input 3 = Strain; Output = Flow stress in Mpa

VI. CONCLUSION

A neural network and a neuro-fuzzy model for predicting the behaviour of Ti-6Al-4V alloy under isothermal forging condition, and analysing 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. The three most important conclusions that can be drawn from the present work are:

1. The application of neuro-fuzzy model can assist in more effective trial and training of network model developed .
2. Neuro-fuzzy models have higher learning precision and generalisation capability and can more accurately predict the behaviour of Ti-6Al-4V alloy than Back-propagation neural network model developed for the same condition.
3. The use of neuro-fuzzy model can reduce the learning time by self adjusting the dynamic

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parameters and can converge more rapidly.

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