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Modelling of flow curve of IF steel sheets using artificial neural network

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ABSTRACT

Several investigations have established that the formability of sheet metal can be assessed from the stress-strain relationship(Sing,W.M and Rao,K.P[1997]). A true stress-strain curve is frequently called a flow curve because it gives the stress required to cause the metal to flow plastically to any given strain. In this paper the flow curve is used for modelling. A model based on an Artificial Neural Network (ANN) is introduced to reveal the flow curve of IF steel of thickness 0.85 mm non-coated. After using experimental data to train and test it, the model is applied to new data for prediction of the flow curve. Flow curve represents the basic plastic flow characteristics of the material.

1. Introduction

In recent years, there has been a growing interest in applying artificial neural networks, a branch of modern information technology, to engineering fields for solving various complex problems (K.Elangovan [2010]).

In sheet metal forming, it is vital to strictly prevent defects like necking, fracture and wrinkling so as to ensure dimensional accuracy and acceptable aesthetics. Production engineers and researchers have paid much attention to the behavior of defects in sheet metal forming over the last decade. In this investigation ANN is used to model flow curve.

2. Experimental procedure

Tensile tests were carried out using sub size specimens of IF steel of thickness 0.85 non-coated as per standard whose chemical composition is given in table (1). The specimens were tested along the three principal directions, with the tensile axis parallel (0^0) diagonal (45^0) and perpendicular (90^0) to the rolling direction of the sheet on a Hounsfield tonsometer machine. The change in width and thickness of the specimen was measured and tabulated for all the three specimens of different orientations. The standard tensile properties were determined from the load elongation data obtained from these tests.

3. Artificial neural network

A neural network is a nonlinear dynamic computational system where, rather than relying on a number of predetermined assumptions, data is used to form the model. Neural networks have traditionally been viewed as simplified models of neural processing in the human brain (Tosun[2002]) .

One of the advantages of using the neural network approach is that a model can be constructed very easily based on the given input, output and trained to accurately predict process dynamics (Wang,J. [2000] and Veerababu [2009]). This technique is especially valuable in processes where a complete understanding of the physical mechanisms is very difficult or even impossible to acquire, as in the case of sheet metal forming process. The neural network learns by using training data. Input variables are supplied and the resultant output is compared with the desired output. The network then adjusts the interconnection weights between layers. This process is repeated until the network performs well on the training set. The network can then be assessed on data not included in the training set, the validation data, to estimate its performance in order to achieve better network convergence.

Neural network is a logical structure with multi-processing elements, which are connected through interconnection weights. The knowledge is presented by the interconnection weights, which are adjusted during the learning phase. There are several algorithms available among which the Levenberg–Marquardt algorithm (trainlm) will have the fastest convergence (Sivasankaran,S.[2009]). In many cases, trainlm is able to obtain lower mean square errors than any of the other algorithms tested. This Back Propagation network is a multilayer of the network architecture including the input layer, the hidden layers and the output layer. Layers include several processing units know as neurons. They are connected with each other by variable weights to be determined. In the network, the input layer receives information from external source and passes this information to the network for processing. The hidden layer receives from the input layer, and does all information for processing. The output layer receives processed information from the network and sends the results to an external receptor.

4. Back propagation (BP) network

It is very difficult to predict the output characteristics of the sheet metal forming processes accurately by mathematical equation. On the other hand ANN is most powerful technique to model the flow curve of IF sheet metals. There exist many different architecture and learning algorithms for neural network models. Most successful and powerful network is three layer back propagation network design (Cheng,P.J.[2000]) and is described with the help of flow diagram as shown in figure (1).

5. Model description

In the development of a multilayer neural network model, several decisions regarding number of neuron(s) in the input layer, number of hidden layers, number of neuron(s) in the

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hidden layer(s) and the number of neuron(s) in the output layer and optimum architecture have to be decided. The experimental values of engineering strain (e) and engineering stress(s) of IF steel obtained from tensile test are given as input parameters to ANN model. The output parameters are the true stress(σ) for 45^0 orientation and 90^0 orientation. The input and output data set of the model is illustrated schematically in figure(2).

6. Data normalization

In order to avoid suppress of the influence of the smaller value from higher valued input variables, both the input and output variables are normalized within the range -1 to 1 before the training of the network (Mallinov,S.[2001]and Hosseini,M.[2008]). The normalized values (x_n) for each raw input / output dataset (di) are calculated as

$$x_n = \frac{2(d_i - d_{min})}{d_{max} - d_{min}} - 1 \quad (1)$$

where d_{max} and d_{min} are the maximum and minimum values of raw data.

7. Neural network design and training

The generalization capability of the neural network is essentially depending on (i) selection of the appropriate input / output parameters of the system (ii) the distribution of the data set and (iii) the format of the presentation of the dataset to the network. The input parameters are engineering stress and strain while the output parameters are the true stress (σ) for 45^0 orientation and 90^0 orientation. In this study two-third of the experimental dataset has been considered for training and one-third of the experimental dataset has been used for testing. Before training the network the input/output dataset were normalized within the range of ± 1 using equation (1). The standard multilayer feed forward back propagation hierarchical neural networks were designed with MATLAB 6.1, a Neural Network Tool box. The networks consist of three layers the input, the hidden and the output layers. Now the designed network has two input neurons and two output neurons. In the network, each neuron receives total input from all of the neurons in the proceeding layer as

$$net_j = \sum_i w_{ji}^n (x_i)^{n-1} \quad (2)$$

where net_j is the total or net input, x_i^n is the output of the node j in the n^{th} layer and w_{ji}^n represents the weights from node i in the $(n-1)^{th}$ layer to node j in the nth layer. A neuron in the network produces its input by processing the net input through an activation (transfer) function which is usually non-linear. There are several types of activation functions used for BP. However the tan-sigmoid transfer function is mostly used which is assigned in hidden layer(s) for processing the input as

$$f(x) = \frac{2}{1+e^{-x}} - 1, \quad \text{range } (-1, 1) \quad (3)$$

and purelin a transfer function calculates a hidden layers output from its net input which is assigned for output layer as

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} - 1, \quad \text{range } (-1, 1) \quad (4)$$

the weights are dynamically updated using the BP algorithm. The network has been trained with Levenberg-Marquardt algorithm. This training algorithm has been selected due to its high accuracy in similar function approximation. Default training parameters available in MATLAB 6.1 has been set for training the dataset. In order to judge the performance of the network, the average error (MSE) has been calculated as :

$$E_p = \sum_{P=1}^{P}\sum_{K=1}^{K}(dp_k - Op_k)^2 \quad (5)$$

where dp_k and Op_k are the desired and calculated output for K^{th} response respectively. The 'K' denotes the number of neuron in output of network and 'p' is the total number of instances (epochs). Then the problem of determining the optimal number of hidden neurons is a crucial one. Several structures have to be considered with different numbers of hidden neurons to determine the best configuration. After training, it is denormalized and compared with the experimental data. The denormalized values (x_i) for each raw output data set was calculated as

$$x_i = \frac{(x_n + 1)(d_{max} - d_{min})}{2} + d_{min} \quad (6)$$

where d_{max} and d_{min} are the maximum and minimum values of raw data respectively.

Table – 1
Chemical Composition of IF Steel (in weight %)

Thickness	C	Mn	Si	S	P	Al	N (ppm)	Ti	B
0.85 non coated	0.003	0.33	0.013	0.0 06	0.04	0.04	32	0.044	0.0007

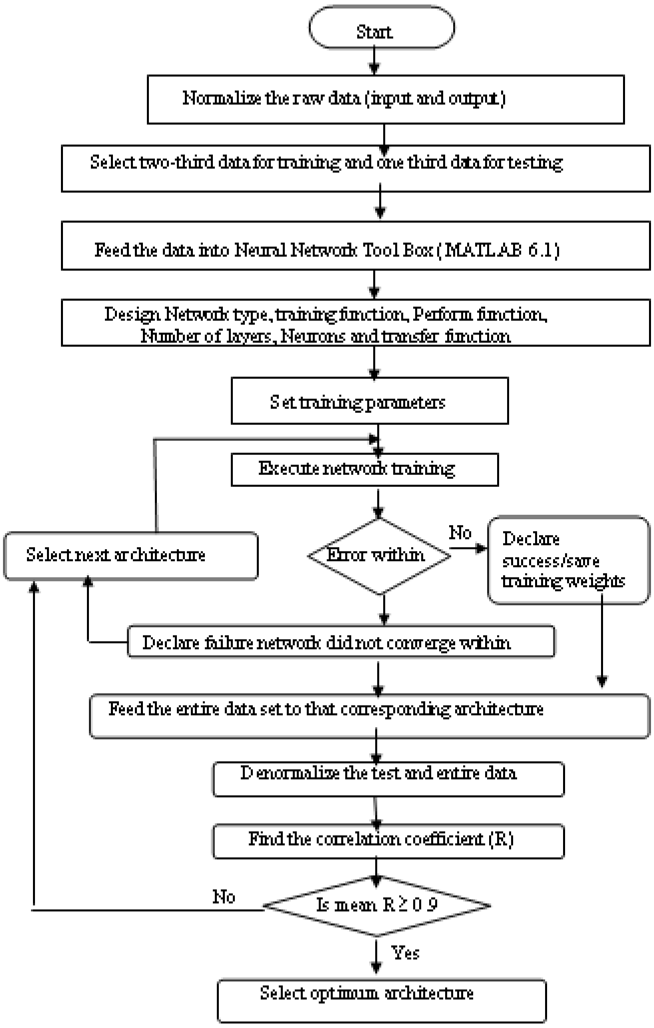
Table – 2
Correlation coefficient between the network predictions and the experimental values using the test dataset for different networks and training parameters of IF steel sheet

Network architecture	MSE	Mean Correlation-45^0	MSE	Mean Correlation-90^0
2-4-4-1	8.19483E-007	0.8790	0.000935423	0.7627
2-5-5-1	2.41105E-006	0.9900	1.58333E-007	0.9866
2-6-6-1	3.12267E-010	0.9927	4.87513E-008	0.9884
2-7-7-1	2.71396E-008	0.9922	8.72114E-009	0.9878
2-8-8-1	**9.45179E-006**	**0.9949**	**8.43316E-008**	**0.9886**
2-9-9-1	1.24901E-006	0.9801	2.39627E-007	0.9765
2-10-10-1	1.36915E-007	0.9840	2.33985E-008	0.9879
2-11-11-1	4.41284E-009	0.9858	2.65135E-008	0.9883
2-12-12-1	2.99518E-007	0.9934	1.42094E-007	0.9854
2-13-13-1	5.93136E-009	0.9914	3.20224E-010	0.9859

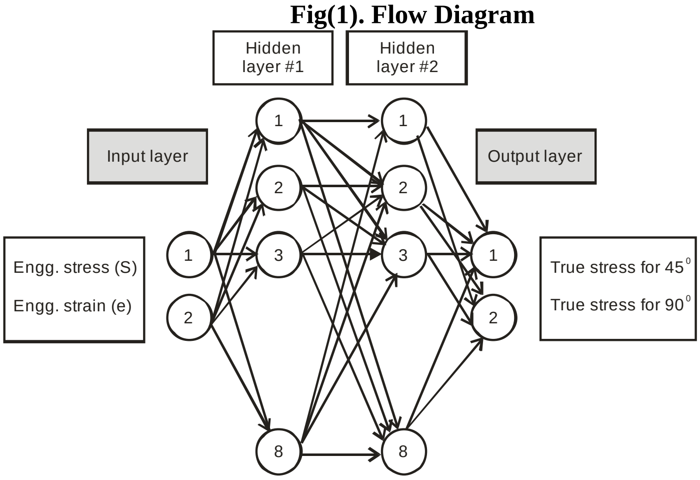
8. Results and discussion

The main objective of the present work is to study, analyse and model the flow curve of an IF steel of thickness 0.85, noncoated sheets. Engineering stress and strain values of 0^0 orientations were used for training and 45^0 & 90^0 were tested. In this analysis the experimental values were agreed with the ANN predicted values. The flow curve (true stress Vs true strain) by experimental and ANN model were same from figure (3) and figure (4).

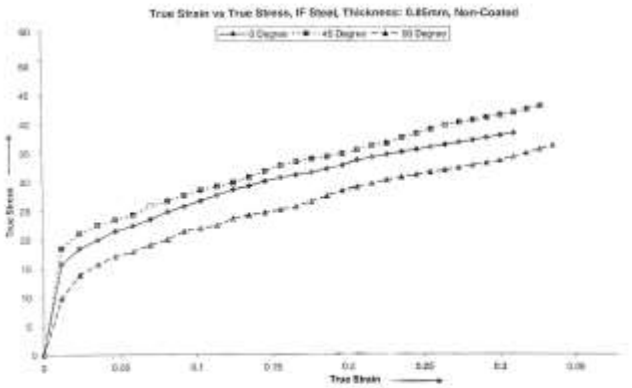
The performance capability of each network has been examined based on the correlation coefficient. In order to decide the optimum structure of neural network, the rate of error conveyance was checked by changing the number of hidden neurons and number of hidden layers. From Table 2, it is identified that the networks with two hidden layers of eight neurons in each layer produced the best performance for each of the output parameters (2-8-8-2). It has the mean correlation coefficient of 0.9949 and 0.9886.



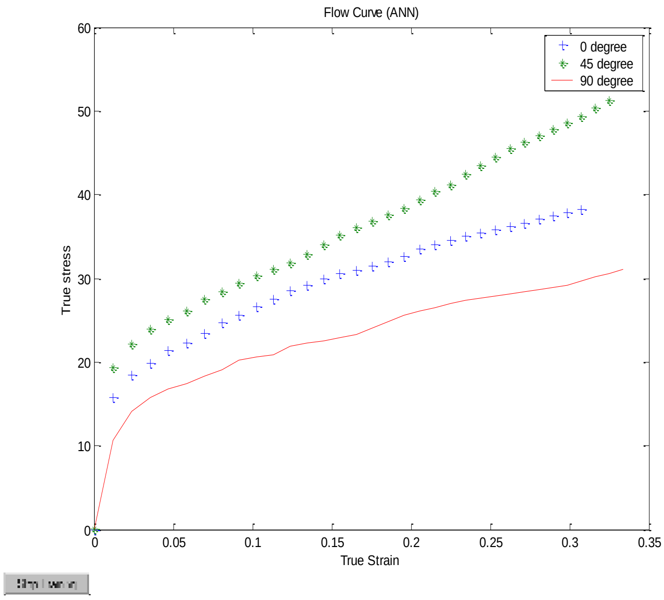
Fig(1). Flow Diagram



Fig(2). Schematic illustration of neural network model



Fig(3) Experimental Flowcurve



Fig(4) ANN Flowcurve

Conclusion

Thus network having two hidden layers of eight neurons in each (2-8-8-2), trained with Levenberg-Marquardt algorithm, has selected as the optimum network. It is also observed that the increase in the number of neurons in the hidden layer had significant improvement on the performance of the networks and then the performance is decreased. The correlation between the predicted values of the optimum neural network model and the experimental data for prediction of true strain and true stress using the entire data set.

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