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PREDICTION OF MECHANICAL PROPERTIES OF TO HEAT TREATMENT BY ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In such a study, for the analysis and simulation of the correlation between the mechanical properties and T_6 heat treatment parameters of AL-357 alloy, an artificial neural network (ANN) model has been developed. The input parameters of the model are composed of T6 heat treatment parameters such as temperature and time of solution treatment, quench and artificial aging. The outputs of the ANN model consist of mechanical property parameters, that is the ultimate tensile strength, yield strength and elongation percentage. The model can be used to calculate the properties of AL-357 alloy as a function of T_6 heat treatment variables. Using the model, the individual as well as the combined effect of inputs on mechanical properties of AL-357 alloy is simulated. The present study attained a good performance of the ANN model, and the results are consistent with experimental knowledge. Explanation of the achieved results from the materials science engineering point of view is attempted. The developed model can be utilized as a guideline for further heat treatment development.

Key Words: Artificial neural network, T_6 Heat treatment, Al-357 alloy, Ultimate tensile strength, Yield strength, Elongation.

INTRODUCTION

The cast Al-Si-Mg alloys are used broadly in a various aerospace, automotive, structural and engineering applications. The Al-357 alloy is of good fatigue, excellent castability and corrosion resistance properties. Such a alloy system is utilized in the T_6 heat treatment condition, which

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includes solutionizing at high temperature, quenching and artificial aging (Kashyap *et al.*, 1993; Kumar *et al.*, 2007). The ANNs are considered to be mathematical modeling tools particularly useful in the field of prediction and forecasting in complex settings. In spite of the fact that several network architectures and training algorithms exist, the feed-forward neural network with the back-propagation (BP) learning algorithm is used much more commonly (Reddy *et al.*, 2005; Rajabi *et al.*, 2012). An input and output layer along with as many units as their related number of variables is defined in a Back-propagation neural networks (BPNN) model. There exists hidden layers in-between the input and output layers, each including a certain number of nodes (or units). Such an algorithm is named as back-error propagation or back propagation (BP) when the correction mechanism begins with the output units and propagates backward via each internal hidden layer to the input layer. The application of neural networks in the materials science engineering research has recently garnered attention in the research literature (Hn Bhadeshia, 1999; Reddy *et al.*, 2009). The main aim of the current investigation is, therefore, to develop a neural network model, to be able to predict the mechanical properties for T6 heat treatment, and the relationship of the properties in terms of these input variables.

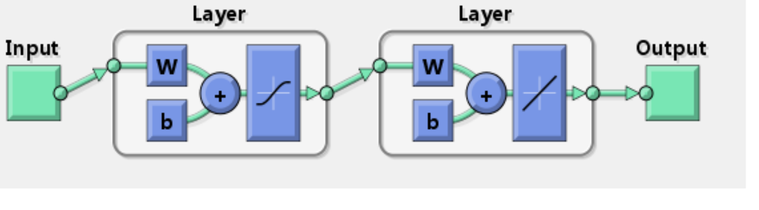
EXPERIMENTAL PROCEDURE

The T_6 heat treatment steps carried out in the respective samples were as follows respectively:

A range of solution treatment temperature at 525 -550°C between 8- 12 h, quenching through water at various temperatures, and also artificial aging treatment at 150-170 °C for 3-8 h. In the present investigation, the feed-forward multilayer Perceptron was utilized and trained by back propagation algorithm via Matlab software. The time and temperature for solution treatment, quench and artificial aging steps were used as inputs, mechanical properties like ultimate tensile strength, yield strength and elongation were the outputs of neural network model.

The transfer function chosen for the network's hidden layers was the sigmoid function. A typical sigmoid curve is relatively flat at both ends, and is of a rapid rise in the middle. Also pure line function was chosen for the output layer. If the last layer of a multilayer network is of sigmoid neurons, then the outputs of the network are restricted to a small range. If linear output neurons are used, then the network outputs are able to take on any value (Zakeri *et al.*, 2007). In this study, regarding Fig 1, the two-layer tan sig /pure line network has been planned.

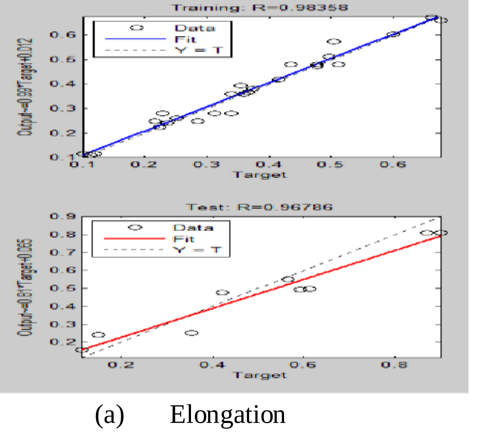
Figure-1. The two-layer tan sig /pure line network



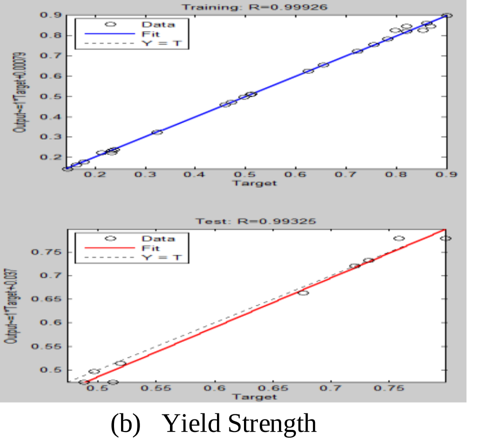
RESULTS AND DISCUSSION

In this investigation, the optimal parameters of the network are identified on the basis of the minimum mean sum square (MSE) error. It has been observed that in Fig. 2(a), (b), and (c) the majority of the outputs including ultimate tensile strength, yield strength and elongation reflect a reasonably accurate prediction (nearly 99%) in training model . In addition , in order to test the data that have never been used by the model, the ANN gives a reasonable forecasting as training step. For instance, it can be observed that there exists a less variation between actual and predicted values as shown in Fig. 2(b) with $R_{testing}$=0.993. Yet, a model with a minimum MSE may not be sufficient in order to remove the possible uncertainty in choosing the model structure. The network training was perpetuated as long as the error goal was achieved and stopped after about 1100 epochs (an epoch is one complete pass through a set of inputs and target patterns while training the network). Because the back-propagation algorithm applied in such a study is essentially a gradient descent method, to reach the minimum value for the error function takes a long iterative procedure and consequently a greater number of epochs. For running a set of unseen test data (10 data sets), the trained neural network model was applied.

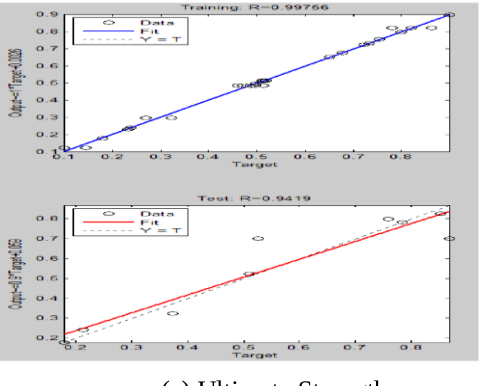
Figure- 2. The results of structure of 6-10-1 for outputs.



(a) Elongation



(b) Yield Strength



(c) Ultimate Strength

In order to investigate the effect of neuron number on the Prediction results, the trial-and-error procedure via five neurons in the hidden layer and further (5, 8, 10, 15, and 20) was applied. In fact The BPNN structure of one hidden layer with a learning rate of 0.3 and a momentum rate of 0.6 was trained by various hidden neurons which started from 5 to 20. In table.1, it has been seen that a network with 10 neurons in one hidden layer supplied a much better mapping. After the number of neurons was increased to optimum value of 10 or more the performance was found deterioration. This might come from over parameterization of the network, since the number of connection weights increases when the number of neurons is on the rise. Likewise, it depicts the variation of $R_{training}$ and $R_{testing}$ for mechanical properties with the number of various neurons in the hidden layer. As the number of neurons increased, the $R_{testing}$ value increased up to 10 hidden neurons and then progressively there was a decrease following a further increase of hidden neurons. Excellent convergence was seen in the 10 neurons of the hidden layer, and a value of $R_{training}$ of 0.985, 0.999 and 0.997 for elongation, yield strength and ultimate tensile strength was obtained and also their $R_{testing}$ was achieved around 0.968, 0.993 and 0.942 respectively. As regards table 1, it is obvious that the convergence is better for the 10 neurons in hidden layer compared to the various amounts of neurons in the hidden layer. Therefore, for further training aimed at optimizing other parameters, 10 hidden neurons along with one hidden layer (6-10-1) have been chosen.

Table-1. A value of $R_{training}$ and $R_{etesting}$ for different networks.

R	Net type	6-5-1	6-8-1	6-10-1	6-15-1	6-20-1
$\mathbf{R_{training}}$	Elongation	0.923	0.950	0.984	0.944	0.940
	Yield strength	0.973	0.980	0.999	0.970	0.980
	Ultimate tensile strength	0.935	0.990	0.998	0.995	0.995
$\mathbf{R_{testing}}$	Elongation	0.348	0.782	0.968	0.778	0.128
	Yield strength	0.422	0.827	0.993	0.893	0.410
	Ultimate tensile strength	0.465	0.683	0.942	0.847	0.756

If the architecture is too small, the network may not be of sufficient degrees of freedom in order to learn the process acceptably. Likewise, if the network is too large, it may not be converged within a training or it may over cover the data. It should be taken into consideration that if the network is trained properly, then it has learned to be able to model the function relating the input variables to the output variables and also can be applied in order to make predictions in places where the out-put is not known. Such ability is labeled as a generalization. To evaluate the generalization capability of the trained network, the test set was taken in this investigation.

CONCLUSIONS

Quenching rate is a key factor to determine the mechanical properties. A fast rate induces a greater vacancy concentration increasing the heterogeneous nucleation of Mg_2Si particles. Outstanding convergence was observed in 10 hidden neurons in the hidden layer, and a value of $R_{training}$ of 0.985, 0.999 and 0.997 for elongation, yield strength and ultimate tensile strength respectively was achieved and also $R_{testing}$ was obtained around 0.968, 0.993 and 0.942 for elongation, yield strength and ultimate tensile strength respectively. The network may not be of sufficient degrees of freedom to learn the process correctly when the architecture is too small On the other hand, if the network is too large, it may not converge during training or it may over fit the data.

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