MODELING THE T_6 HEAT TREATMENT OF Al-Mg-Si ALLOY BY ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Artificial Neural Networks are mathematical modeling tools which has recently been used in the field of prediction and forecasting in engineering applications. In this study the feed-forward neural network with the back-propagation (BP) learning algorithm had been applied. Quench and artificial aging as well as solution treatment temperature and time have been defined as the input parameters of ANN. The output layer of the ANN model consists of hardness. Investigates showed better results when network had a hidden layer with 10 neuron compared to 5 neurons. This model can predict the hardness within an average error of 1% from the experimental values. This simulated ANN model seems to possess an edge over existing constitutive model, like hyperbolic sine equation, and has a great potential to be employed in industries.

Keywords: Artificial neural network, T_6 heat treatment, Al alloy, Hardness.

INTRODUCTION

Aluminium is increasingly attractive due to its strength and stiffness to weight ratio. Al-Mg-Si alloys are age hardenable and widely used in both cast and wrought forms. Strengthening of Al-Mg-Si alloys is based on a precipitation hardening process. Their importance and significant age-hardening response has provoked numerous studies of precipitation in these alloys. Cast Al-357 (Al-0.5wt% Mg-7wt%Si) alloy also possesses excellent castability and good fatigue and corrosion resistance properties. It has widespread applications for structural components in the automotive, aerospace and general engineering industries because of its excellent castability, corrosion resistance and particularly high strength-to-weight ratio in the heat-treated condition. However, the use of this cast alloy is still limited in comparison with wrought Al alloys, even though casting is a more economical production method. This is partly because cast Al alloys may contain defects such as porosity, oxides and other inclusions, which significantly affect the mechanical properties of the cast Al components (Imurai et al. 2010). In order to further improve the mechanical properties of cast components these alloys can be heat treated. Various heat treatment cycles, e.g. different combinations of temperatures and times, are used depending on the casting process, the alloy composition and the desired mechanical properties. The aluminum association has standardized the definition and nomenclature for heat treatment. A typical heat treatment applied to sand and gravity die-cast Al–Si-mg alloys is the T6 condition, which involves the following stages.

Firstly, solution treatment at a relatively high temperature to dissolve Cu and Mg-rich particles formed during solidification to achieve a high and homogeneous concentration of the alloying elements in solid solution. Secondly, quenching, usually to room temperature, to obtain a supersaturated solid solution of solute atoms and vacancies. Finally, Age hardening, to cause precipitation from the supersaturated solid solution, either at room temperature (natural ageing) or at an elevated temperature (artificial ageing) (Sjölander&Seifeddine 2010).

The ANN modeling can be an excellent approach in simulating the manufacturing processes and predicting their out-put. That is because ANN exhibits a significant ability in managing, optimizing, estimating and controlling various parameters so the flexibility and simplicity of neural networks have made them a popular modeling and forecasting tool for research areas in recent years. Artificial neural network (ANN) is a network with nodes or neurons analogous to the biological neurons. The nodes are interconnected to the weighted links. The weights are adjustable and can be trained by learning and training process and training treatments. If correct weights (W) can be trained, then an ANN can do an exceptional function. ANN is able to receive inputs patterns in order to produce a pattern on its outputs that are correct for that class. Therefore, a number of variations of the standard algorithm have been developed to determine the correct value of weights (Dehghani &Nekahi 2010 & Kumar et al. 2007). A variety of different neural network models have thus developed, among which the back-propagation (BP) network is the most widely adopted in the present .A BP algorithm is a kind of generalized form of the least mean-squares algorithm usually used in engineering. But the basic BP algorithm is too slow for most practical applications. In order to speed up the algorithm and make it more practical, several modifications have been proposed by researchers. The research on faster algorithm falls roughly into two categories. One involves the development of heuristic techniques such as the use of momentum and variable learning rates. The other has focused on standard numerical optimization techniques such as the conjugate gradient algorithm and the Levenberg-Marquardt algorithm. Among these algorithms, Levenberg-Marquardt algorithm is the most rapid for medium networks (Xu et al. 2007, Reddyet al. 2005 and Lin et al. 2009). It should be noted that given a proper number of hidden layer units, neural networks can manage any non-linear function to an arbitrary degree of accuracy by making a network based on relatively simple functions (Dehghani & Nekahi 2010).

METHODOLOGY

The T6 Heat Treatment

The knowledge of a specific field is implicated in the existing training samples, so an appropriate dataset with good distribution is significant for reliable training and performance of neural networks. To ensure reasonable distribution and enough information containing of the dataset, heat treatment techniques of Al-357 alloy are covered with different solution treatment time and temperatures and artificial aging time and temperatures. The total samples reach 50 .Therefore, the T6 heat treatment steps carried out in the respective samples were as follows respectively:

A range of solution treatment temperature at 490 -545°C between 3- 6 h , quenching through water at various temperatures , and also artificial aging treatment at 130-155 °C for 3-6 h .

Developing the ANN Model

Quench and artificial aging as well as solution treatment temperature and time play important roles in influencing mechanical properties like hardness in T6 heat treatment. The target of this research is to establish nonlinear relationships between the input parameters and the output parameters by the usage of BP networks. So to model T6 heat treatment of Al-Mg-Si alloy, temperature and time of quench and artificial aging as well as solution treatment has been defined as input and hardness as outputs in network. In this paper, three layers BP neural networks, includes one input layer, one hidden layers and one output layer, are used for predicting hardness according to figure 1. Sigmoid and pureline transfer function was employed for hidden layers and output layer, respectively. Multilayer feedforward network models with one hidden layer can approximate any complex nonlinear function provided sufficiently many hidden layer neurons are available. Therefore, in this study, multilayer feedforward network models containing one hidden layer were used. Determination of optimum number of the hidden layer neurons is very important in order to predict accurately a parameter using by ANNs. However, there is no theory how many hidden layer neuron need to be used for a particular problem. The best approach to find the optimum number of hidden neurons is to start with a few numbers of neurons and then slightly increasing the number of neurons. During this process for each hidden neuron number the performances of the network models are monitored according to chosen performance criteria. Finally, In order to relieve the training difficulty and balance the important of each parameter during training process, the examinational data were normalized. It is recommended

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that the data be normalized between slightly offset values such as 0.1 and 0.9. One way to scale input and output variables in interval [0.1, 0.9] is as (Xu et al. 2007):

$P_n = 0.1+(0.9-0.8)\,(P - P_{min})/\,(P_{max} - P_{min})$................................ (1)

Where P_n is the normalized value of P, which is of a maximum and a minimum value given by P_{max} and P_{min}, respectively.

Table 1.Hardness values in different T6 heat treatment

Sample	Artificial aging treatment		Solution treatment		Hardness(HV)
	Temperature(°C)	Time(hr)	Temperature(°C)	Time(hr)	
B_1	155-165	6	535-545	6	**96**
B_{12}	155-165	6	535-545	3.15	**83**
B_{14}	155-165	6	535-545	6	**96**
B_{15}	155-165	5.45	535-545	6	**95**
B_{16}	155-165	5.3	535-545	6	**90**
B_{25}	155-165	3.15	535-545	6	**88**
B_{27}	155-165	5.45	535-545	5.45	**95**
B_{38}	155-165	3	535-545	3	**88**
B_{40}	155-165	6	535-525	6	**93**
B_{43}	155-165	6	490-505	6	**90**
B_{44}	145-155	6	535-545	6	**90**
B_{45}	135-145	6	535-545	6	**89**
B_{46}	130-135	6	535-545	6	**83**
B_{47}	150-155	6	535-525	6	**94**
B_{50}	135-140	6	490-505	6	**93**

RESULT AND DISCUSSION

Collecting the Experimental Data

After employing the designed T6 heat treatment process, the hardness amounts is obtained in different condition. Table 1 shows the some results obtained from the preliminary analysis of this kind of heat treatment process on the Al-Si-Mg alloy in different condition. As already mentioned, to ensure reasonable distribution and enough information containing of the dataset, heat treatment techniques of Al-357 alloy are covered with different solution treatment time and temperatures and artificial aging time and treatment temperatures. Input parameters and output parameter based on equation .1 were normalized to utilize in ANN model.

Neural-Network Modeling

In terms of simulating the heat treatment process using ANN, one should consider that the physical simulation by experimental work not only is time consuming but also it cannot overcome many errors encountered at a laboratory scale. Therefore, a well-established ANN modeling can allow predicting heat treatment with the capability for replacing even mathematical modeling. The current ANN model adopts a non-linear mapping method to establish models according to input and output data directly. So to achieve such as model, data set should be chosen for training and testing steppes.

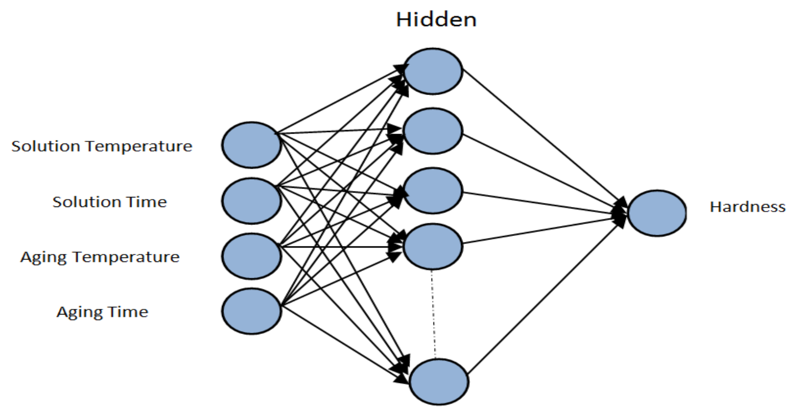


Figure 1.The schematic of inputs and output in multilayer perceptron ANN model

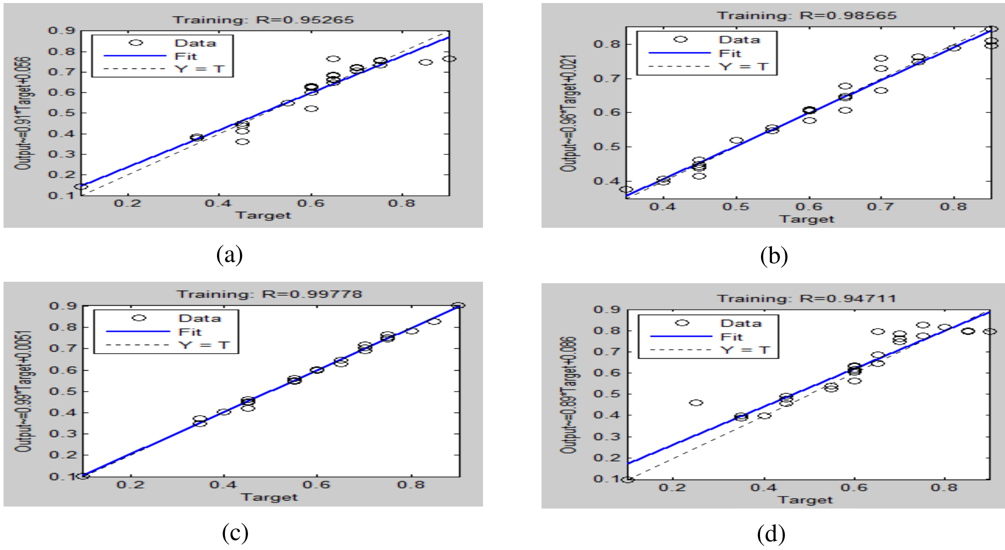
Training and verifying

To train and verifying , four neurons for the input layer and 5,8,10,15 and 20 neurons for the first hidden layer as well one neurons for the output layer were designed. This combination resulted in a cascade-forward neural network that requires a back-propagation algorithm. According to this design, the automatic initial weights were chosen because of its simplicity and reliability for a variety of applications. Then, 70% data set in experimental conditions were considered for training and verifying the network. These results were then modeled so that the network could predict the hardness without requiring any further experiments.

The artificial neural networks achieved stable states after 320 cycles of training and the R-value of networks reach 0.936, 0.985, 0.99, 0.997 and 0.947at last, respectively. The verifying results of trained data are shown in figure 2 (a to d). This figure shows that network consist of 15 neuron in hidden layer ,4-15-1 model, resulted in the lowest value of error with R- value 0.997.It is clear that increasing neuron in hidden layer has been cause $R_{training}$ increased but after 15 neuron a decreasing in it had been seen. In general, the training process is always performed by 'trial and error method' and there is no automatic way for that when using artificial neural networks . That is because by changing the learning rates, momentum values and node numbers of hidden layers training iterations are made. The optimum architecture is developed in this way to minimize the errors. The average percent errors and the differences between the given output values and the values after training iterations can be determined when running the neural-network programs. The errors are minimised with more iterations in neural-network programs by using the appropriate learning rates, momentum values and hidden layer nodes (Dehghani&Nekahi 2010).

Prediction step

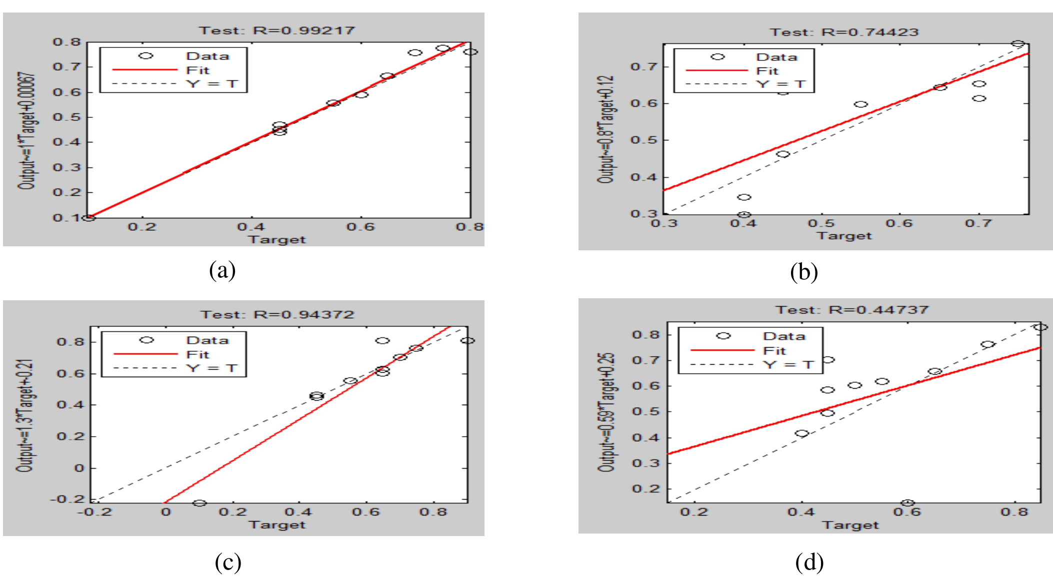
After neural networks are trained successfully, all domain knowledge extracted out from the existing samples is stored as digital forms in weights associated with each connection between neurons (Xu et al. 2007).So remaining 30% data sets are chosen for testing. Figure 3 (a to d) has been shown the results of prediction in testing step using trained networks. From the data in figure 3, it is apparent that optimum of $R_{testing}$ has been achieved for network including 4-10-1 architecture. There exists an increase of $R_{testing}$ associated with increasing amount of neuron in hidden layer but it had increased when hidden layer included more than 10 neuron. Likewise, there were significant differences between obtained results between using 10 and 20 neuron in hidden layer. In these figures, the hardness values predicted by model are compared with those of experimental results. As it is obvious, the values predicted by ANN are in very good agreement with the ones obtained by experimental work. Figure 3 presents the comparison between measured and predicted results for hardness. The agreements between the predicted and measured values indicate that this approach can be very useful in modelling the mechanical properties of hardness in heat treatment technique.



(a) (b) (c) (d)

Figure 2.Verifying results for hardness value of training samples by BP neural network

That is because, in all cases, the prediction values match the measured amounts very well. As earlier mentioned, the complexity of heat treatment process, due to interacting many parameters simultaneously (e.g. material composition, aging and solution time, aging and solution temperature, etc.), can make it difficult to get accurate experimental results in this regard. According to achieved results in training and testing steps, the optimal network architecture is 4-10-1. In terms of the contribution and range of errors pertaining to present results, they can be put in two categories. The first is regarding the characteristics of ANN itself including actuator faults, process component faults, sensor faults, unknown influences like noise or disturbances and errors in the process controller (Dehghani&Nekahi 2010).The second is the location of the changes in testing conditions, non-uniform microstructure in the specimen, inhomogeneity of the mechanical properties in the samples, etc.In this respect, the obtained results can be discussed as follows: First, the use of neural network exhibit excellent accuracy in predicting the mechanical properties out-puts. Secondly, as mentioned already, there are many contributing factors in heat treatment process that cannot be considered in the mathematical modeling but they can be easily incorporated in neural-network modeling.



(a) (b) (c) (d)

Figure 3.Testing step results for hardness value by BP neural network.

Thirdly, the present neural network can predict the mechanical properties directly and in a much more rapid approach comparing to the mathematical modeling such as finite element. These characteristics of present ANN in predicting the hardness value can be very valuable from an industrial point of view. Different network topologies were studied to design a network with the least error and the most accuracy in prediction. Finally, a network with different hidden layers neuron with a sequence of tansigmoid, and linear activation functions offered the least error and was therefore selected for present neural network.

CONCLUSIONS

Artificial neural network is one of the useful tool to model T6 heat treatment parameters. The conclusion for modeling of T6 heat treatment of Al-Si-Mg alloy by ANNs is summarized as follows:

1. The none-line relationship of microstructure and properties vs. heat treatment temperatures could be built by BP artificial neural networks. The tested results show the well-trained BP neural networks can precisely predict hardness (Hv) of Al- 357 alloy according to temperature and time of solution and artificial aging treatments.
2. From the $R_{training}$ results, the low error relate to using 15 and 10 neuron in hidden layer, respectively ,while based on $R_{testing}$, hidden layer containing 10 neuron is of highest R-value. Therefore according to the achieved results in training and testing steps, the optimal network architecture is 4-10-1.
3. The training process is always performed by 'trial and error method' and there is no automatic way because of changing the learning rates, momentum values and node numbers of hidden layers training iterations are made.
4. The complexity of T6 heat treatment process, due to interacting many parameters simultaneously (e.g. material composition, aging and solution time, aging and solution temperature, etc.), can make it difficult to get accurate experimental results in this regard.

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