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DETERMINATION OF HARDNESS OF PRE-AGED AA 6063 ALUMINUM ALLOY BY MEANS OF ARTIFICIAL NEURAL NETWORKS METHOD

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Abstract- A lot of experiments must be conducted in order to find an appropriate technology for the calculation of strength of the materials, which wastes both man power and money. For this reason artificial neural networks (ANNs) have been used to search the optimum technology proper for pre-aged AA 6063 aluminum alloy. In this study, ANNs were used to compare experimental results and test data were used for teaching of the ANNs. This paper examines the changes in the hardness of AA 6063 alloys when heat treated at different pre-aging treatments. The alloy was solution treated for 1 hour at 525±3 ^{0}C and quenched in water. After quenching, samples were subjected to five different pre-aging times, 2 hours, 1 day, 3 days, 7 days. On the other hand, some specimens were not pre-aged. Artificial age temperatures were selected as 160 ^{0}C and 180 ^{0}C. The hardness values of these under-aged alloys were measured. When the pre-aging time was 7 days, the hardness values of the specimens increased. An excellent correlation was found between experimental hardness results and ANNs hardness results.
Key words- AA 6063, Pre-Aging, Artificial Neural Networks, Hardness.

1. INTRODUCTION

Some aluminium alloys can be hardened by precipitation hardening hardness can be increased 40 times compared to high purity aluminium with convenient alloying and heat treatment [1]. Aluminum alloys have low density, high strenght, excellent resistance to corrosion (one-third of the corrosion resistance of iron) and good surface finish. The strength of aluminum alloys was increased by precipitation hardening method first time by Wilm in 1906. Precipitation hardening is a very important concept in development of aluminum alloys [2-5].

In the recent years, Al-Mg-Si alloys have found increasing use in automotive technology to reduce the weight of cars. AA 6063 aluminum alloys are as structure members such as window frame, glazing bars, irrigation tubing, and car body. Age hardenable Al-Si-Mg alloys are expected to be strengthened by precipitation hardening. The two step aging behavior of Al-Si-Mg alloys has been investigated by many researchers [6-10].

Precipitation hardening or age hardening [2], is achieved by a solution treatment and quenching of an alloy of which consists of preparation of a solid solution at high temperature. Than precipitation by quenching and ageing at a low temperature. Aluminium alloys and copper beryllium alloys are common examples of the precipitation hardening. For precipitation hardening to occur, the second phase must be soluble at an elevated temperature but must exhibit a decreasing solubility with decreasing temperature.

In contrast, the second phase in dispersion-hardening systems has a very little solubility in the matrix, even at elevated temperatures. Usually there is atomic matching, or coherency, between the lattices of the precipitate and the matrix, while in dispersion-hardened systems there is generally no coherency between the second-phase particles and the matrix. The requirement of a decreasing solubility with temperature limits the number of useful precipitation-hardening alloy systems [11, 12].
Mechanical properties of Al-Mg-Si alloys change with the concentration of Mg_2Si . The Mg/Si rate is 1.73 which this rate is very important in preaging treatments on the precipitation behavior of aluminium alloy 6063. If the concentration of mg_2si is lower than %1, the effect of preaging is positive in Al-Si-Mg alloys. Darward stated that alloys with Mg_2Si concentrations of 0.57; 0.77 and 0.89 had been positive influenced from preaging treatment [13].
It is accepted that all of the Mg is used for formation of Mg_2Si. Mg_2Si is 0.84 for this paper. If the Mg/Si is 1.73 [10],

From Table1,
Si= 0.53 /1.73, Si= 0.31, Mg_2Si= 0.84

In this study, experimental and artificial neural networks values of the hardness results have been used to investigate the effects of different preaging treatments on the precipitation behavior in an aluminum alloy 6063. In 1943, Mc Cul Loch and Pitts developed a model of a neuron, which later on, with some difficulties encountered in the 1970s, was developed into artificial neural networks (ANNs). ANNs are systems enable supervised or unsupervised learning and numerical data prediction. In supervised learning, the input components are accompanied with the corresponding output components. The network is to learn the correspondence between the former and the latter. During unsupervised learning, the network is to classify the data by introducing certain generalized measure of a distance between the data vectors. This second group belong various art architectures (adaptive resonance theory) developed at 1987 by Carpenter and Grossberg, who recently successfully for the prediction of the properties of concrete materials [14-15]. In this experimental study, this method was used for the hardness test determination of mechanical properties.
Hardness is the resistance of a metal to plastic deformation, which is usually measured by indentation. Hardness is not a fundamental property of a material but is related to the elastic and plastic properties. A quick measure of resistance is given by the hardness test. The hardness value obtained in this particular test provides only a comparison between materials or treatments. Heat treatment usually results in a change in hardness of the material.

2. EXPERIMENTAL DETAILS

In this study, AA 6063 alloy (Al-Mg-Si) was used as test material. The alloy was supplied from ETIALUMINYUM (TURKEY). The chemical composition of the used material is given in Table 1.

Table 1. Chemical Compositions of the Materials Used in the Experiments.

Si	Fe	Cu	Mn	Mg	Zn	Ti	Ni	Pb	Sn	Al
0.506	0.245	0.012	0.005	0.531	0.009	0.008	0.014	0.003	0.005	Balanced

The specimens were prepared from AA 6063 aluminum alloy. All specimens were annealed in a furnace at 380±3 ^{0}C for 1 hour, before analysis. Then, the specimens were kept in the furnace at 525±3 ^{0}C for 1 hour for solution treatment. Afterwards, the specimens were quenched in water at room temperature. Pre-aging time were selected as 2 hours, 1 day, 3 days and 7 days. Some specimens were not pre aged. After all specimens were preaged, artificial aging was applied to some specimens in a furnace at the temperature of 160 ^{0}C and 180 ^{0}C. All the specimens are subjected to hardness test for a period of one hour. Rockwell b hardness measurement method was used to determine the hardness of the materials. Hardness values of samples increased with increasing pre-aging time. The present work investigated the determination of hardness of pre-aged 6063 aluminum alloys by using ANNs.

3. NEURAL NETWORK MODEL

These techniques use a set of processing elements (or nodes) analogous to neurons in the brain. These processing elements are interconnected in a network that can then identify patterns in data as it is exposed to the data. In a sense, the network learns from experience just as people do. This distinguishes neural networks from traditional computing programs, that simply follow instructions in a fixed sequential order. Artificial neural systems are physical cellular system which can acquire, store and utilize knowledge. Currently neural networks can already be of great value in helping to solve many problems.

Artificial neural networks (ANNs) are based on the neural structure of the human brain, which processes information by means of interaction between many neurons. In the past few years there has been a constant increase in interest of neural network modeling in different fields of materials science. The basic unit in the ANNs is the neuron. The neurons are connected to each other with weight factor. A network is usually trained using a large number of input with corresponding output data [16].

Architectures with a large number of processing units enhanced by extensive interconnectivity provide for concurrent processing as well as parallel distributed information storage.

In this study, a multi-layer, feed-forward, back-propagation ANN architecture is used. The multi-layer perception has an input layer, two hidden layers, and an output layer. The input vector representing the pattern to be recognized is incident on the input layer and is distributed to subsequent hidden layers, and finally to the output layer via weighted connections. Each neuron in the network operates by taking the sum of its weighted inputs and passing the result through a nonlinear activation function (transfer function).

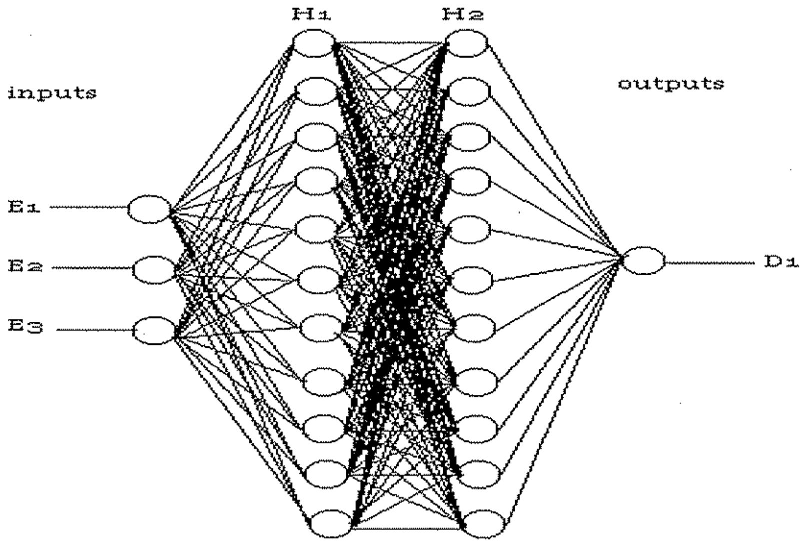

Figure 1. The ANN Architecture.

If o_j^m represent the output of the jth neuron in the mth layer, and W_{ij}^m the weight on connection joining the ith neuron in the $(m-1)$th layer to the jth neuron in the mth layer, then:

$$o_j^m = f\left[\sum_i \left(W_{ij}^m o_j^{m-1}\right)\right], \qquad m \geq 2, \tag{1}$$

Where the function $f(.)$ Can be any differentiable function. In this study the sigmoid function defined below is used as the transfer function.

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

This function limits the outputs o_j^m among 0 and 1. To achieve the required mapping capability, the network is trained by repeatedly presenting a representative set of input/output patterns, with a back-propagation error and weight adjustment calculation to minimize the global error e_p of the network, i.e.

$$E_p = \frac{1}{2}\sum_{j=1}^{n_0}\left(t_{pj} - o_{pj}^m\right)^2 , \tag{3}$$

Where t_{pj} is the target output of neuron j and o_{pj}^m is the computed output from the neural network corresponding to that neuron. Subscript p indicates that the error is considered for all the input patterns.

Minimization of this average sum-squared error is carried out over the entire training patterns. As the outputs o_{pj}^m are functions of the connection weights $\mathbf{w}^m$ and the outputs

o_{pj}^{m-1} of the neurons in the layer $m-1$, which are functions of the connection weights $\mathbf{w}^{m-1}$, the global error e_p is a function of $\mathbf{w}^m$ and $\mathbf{w}^{m-1}$. Here, $\mathbf{w}$ with a superscript refers to the connection matrix. To accomplish this, $\mathbf{w}$ evaluates the partial derivative, $\partial e/\partial \mathbf{w}_{ij}$ and supplies a constant of proportionality as follows:

$$\Delta W_{ij} = \varepsilon\, \delta_{pj}\, o_{pi} \tag{4}$$

where ε refers to the learning rate, δ_{pj} refers to error signal at neuron j in layer m, and o_{pi} refers to the output of neuron i in layer $m-1$. δ_{pj} is given by

$$\delta_{pj} = \left(t_{pj} - o_{pj}\right) o_{pj}\left(1 - o_{pj}\right) \qquad \text{for output neurons,} \tag{5}$$

$$\delta_{pj} = o_{pj}\left(1 - o_{pj}\right) \Sigma_k \delta_{pk} w_{kj} \qquad \text{for hidden neurons,} \tag{6}$$

where o_{pj} refers to layer m, o_{pi} refers to layer $m-1$, and δ_{pj} refers to layer $m+1$. In practice, a momentum term (μ) is frequently added to eq. (10) as an aid to more rapid convergence in certain problem domains. The weights are adjusted in the presence of momentum by:

$$\Delta W_{ij}(n+1) = \varepsilon\left(\delta_{pj}\, o_{pi}\right) + \mu \Delta W_{ij}(n). \tag{7}$$

The ANNs architecture is illustrated in Figure 1, and comprises many simple processing neurons organized in a sequence of layers: input, intermediate (hidden) and output layers. The simulation problem consists of finding a satisfactory relationship between a set of neurons representing the input data and associated known output. The selection of the input parameters is a very important aspect of neural network modeling . All relevant input parameters must be represented as the input data of the neural network. In this study the input data is the information about the testing conditions and the output identifies the failure of the specimen. These involve the input and output layers respectively.

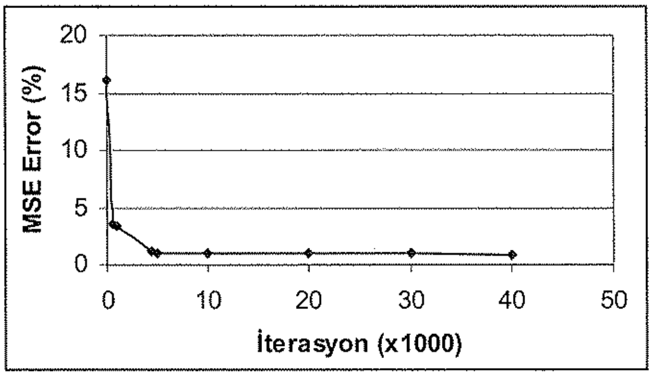

Figure 2. Iteration Number Versus Mean Square Error for Training Non-Linear Correction Coefficient.

For this computation a PC (Pentium II- Intel MMX) was used. The input variables were aging temperatures (160 ^{0}C and 180 ^{0}C), pre-aging and aging times. Output variables were hardness of specimens. 11 neurons was selected in the two hidden layers. Therefore, we have three input variables and an output variable in our application. In neural network applications, input or output values could be reduced to the values of 0-1, which is called the normalization process. Iteration number was selected as 50000. The learning rate and momentum values were selected as 0.9, 0.7 respectively. These values were found from the result of pre-trials. The training was made once for test phase. The mean error was calculated as %2.1 for hardness. Iteration number versus mean square error (MSE) is shown in figure 2. The ANN used architecture is a 3:11:11:1 multilayer architecture as shown in Figure 1.

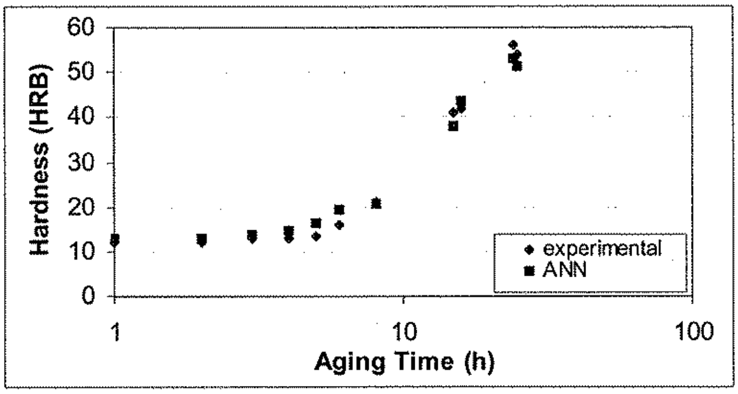

Figure 3. The Comparison of Experimental and ANN Hardness Results at Aging Temperature (160 ^{0}C) for the Specimens Pre-Aged at 1 Day.

12 values were selected for test phase. This specimens were pre-aged for 1 day at room temperature, then they were aged at 160 ^{0}C. Experimental results of hardness results were compared to that of ANN results which shows that the ANN is good enough for the prediction of hardness of materials. In Figure 2, the mean square errors (MSE) in training are presented. The MSE dropped drastically after 5000 iterations. But training continued up to 50000 iterations since we would like to achieve results very close to those obtained by the experiments.

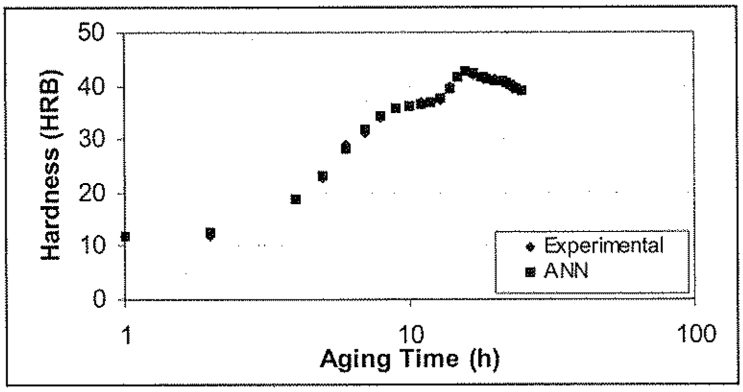

Figure 4. The Comparison of Experimental and ANN Hardness Results at Aging Temperature (180 ^{0}C) for the Specimens Pre-Aged at 3 Days.

4. CONCLUSIONS

Aging behavior of Al-Mg-Si alloys greatly depends on pre-aging treatments. The method of ANN is used alternatively to predict experimental results. Key values obtained by using the experiments were used for training of an ANN. After training, the mean square error became low.

In this study, the hardness of AA 6063 alloy subjected to the various preaging and aging treatments were determined. Before tests, all specimens were annealed in a furnace at 380±3 ^{0}C for 1h. Then, the specimens were kept at 525±3 ^{0}C for 1 hour. They were placed a in solid solution and then quenched at room temperature in water. These specimens were preaged at room temperature. Then specimens were artificially aged at 160 ^{0}C and 180 ^{0}C. Hardness tests were performed for an hour for each specimen. This experimental results were compared with ANN results. Iteration number was selected 50000. 3 input neurons, 11 neurons in the intermediate layers and a output neurons (3:11:11:1) were selected for this study. The learning rate and momentum values were selected as 0.9, 0.7 respectively.

1. At the 6063 aluminum alloy, concentration of mg_2si is lower than %1. Therefore the effect of the preaging is positive in this alloy.
2. The training finished in 30 min. Whereas experimental study took a long time.
3. 2 hours, 1 day, 3 days and 7 days were selected as preaging period. It was found that hardness values increased with the preaging time at experimental results and ANN's results.
4. When artificial age temperatures was concerned hardness values were higher at 160 ^{0}C than 180 ^{0}C.
5. The maximum hardness value was found for the preaged specimen at room temperature for 7 days.
6. The results obtained in ANN application were close to experimental results. 12 values were for test phase. These specimens were preaged for 1 day at room temperature.

Then they were aged at 160 ^{0}C of hardness values were compared between experimental results and ANN results (Figure 3). This shows that the ANN give good .

7. Results for prediction of training phase was illustrated in Figure 4. Specimens were preaged for 3 days and then aged at 180 °C. Experimental results are very close to ANN results.
8. The prediction were in good agreement with the experimental data. A very good performance of the trained neural network was achieved. ANN can be used to find the hardness values of materials.

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