



Research Paper / Makale

Optimization of Tensile Strength of Al Alloys with Mg and Ti

Halil Ibrahim KURT*

*Department of Mechanical and Metal Technologies, Technical Sciences, Gaziantep University, 27310, Gaziantep/Turkey; E-Mail: hiakurt@gmail.com

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Abstract: In this study, the influences of magnesium and titanium elements on the ultimate tensile strength of aluminum alloys were analyzed. The alloys were produced with sand casting method. Magnesium and titanium contents in the alloys were varied from 2 to 14 wt.% and from 1 to 3 wt.%, respectively. Tensile tests were carried out at a tensile speed of 1 mm/min and room temperature. The tensile strength of these alloys was also investigated using the artificial neural network approach. Linear correlations of train and test results were observed to be 99.12 and 91.88%, respectively. It was seen that magnesium has a greater effect than aluminum and titanium on the tensile strength.

Keywords: Al Alloys, Mg and Ti Additions, Tensile Strength

Mg ve Ti ilaveli Al Alaşımlarının Çekme Mukavemetinin Optimizasyonu

Özet: Bu çalışmada, alüminyum alaşımlarının çekme mukavemetine magnezyum ve titanyum elementlerinin etkisi araştırılmıştır. Alaşımlar kum döküm yöntemi ile üretilmişlerdir. Alaşımlarda, magnezyum oranı ağırlıkça %2-14, titanyum %1-3 oranında değişmektedir. Çekme testler oda sıcaklığında 1 mm/dak hızında yapılmıştır. Yapay sinir ağırları yöntemi kullanılarak alaşımların çekme mukavemeti araştırılmıştır. Eğitim ve test sonuçlarının liner korelasyonu %99,12 ve %91,88 olarak tespit edilmiştir. Alaşımların çekme mukavemeti üzerine magnezyumun, alüminyumdan ve titanyumdan daha büyük bir etkiye sahip olduğu görülmüştür.

Anahtar kelimeler: Al alaşımı, Mg and Ti ilavesi, Çekme Mukavemeti

1. Introduction

Aluminum (Al) and its alloys have low density values in comparison to copper, steel and titanium (Ti) alloys. Al-Mg based alloys are commonly used in wide variety of applications in industry. Magnesium (Mg) with very low density of 1.74g/cm³ decreases the density of Al and improves the mechanical properties of Al alloys. Al-Mg alloys containing low amounts of Mg indicate good corrosion resistance, medium strength and good welding characteristics. Because of these properties, they are widely used in shipbuilding and transportation industries. Al-Mg alloys containing higher amounts of Mg have low density values and high compressive strength and they are used in aerospace and automotive industries [1]. Although the cast-ability and strength of Al-Mg are improved by Mg addition to a certain extent, the presence of β -Al₃Mg₂ brittle phase reduces its toughness, corrosion resistance and formability [2]. The size and shape of grains and morphology and distribution of intermetallic affect the mechanical behaviors of Al alloys [3]. Many studies are employed to enhance the mechanical properties of these alloys [4]. One of effective ways to improve the mechanical properties is to add a third element to the composition such as copper, manganese, silicon, zinc and titanium [5]. In this study, we produced Al-Mg alloys with Ti

with different weight ratios by sand casting method [6]. Secondly, all results are examined and analyzed by numerical method. One of statistical analysis method is artificial neural network (ANN) approach. The approach links input data to output data and determining of the optimal architecture of network is one of the challenging steps in NN studies. The architecture consists of layers in the network. A training algorithm is required for a problem solution in NN system. The biases and weights in NN are regulated to minimize the error in the course of the training process [7]. ANN can be solved problems much faster, so it is much popular and a hopeful research field in interpreting experimental works in the last decade years [8].

The tensile strength results of samples are tested for the mechanical properties of specimens. The effects of addition of Mg and Ti (different wt. %) on the tensile strength of Al-Mg as-cast alloys are investigated. ANN approach is also used to investigate the strength of aluminum alloyed Mg and Ti elements in the present work. The main aim is to model the obtained results by using ANN technique and to evaluate the accuracy of the model.

2. Materials and Methods

2.1. Materials

Pure aluminum (99.70 %) and pure magnesium (99.70 %) and titanium tablet (75% pure titanium and 25% flux) are used to prepare the aluminum alloys.

2.2. Methods

Al is first heated up to 750°C using electrical resistance furnace and SiC crucible. Then, Mg and Ti are added into the molten aluminum. Next, the melt is poured into the sand mould after the dross is cleaned off. The melt is stirred and it is degassed by N₂ throughout the casting. After this process, all the alloys are analyzed and UTS of the alloys is determined. In Table 1, the compositions and UTS of the alloys are shown.

Table 1: Compositions and tensile strengths of the alloys

| Exp. No | AL (wt.%) | Mg (wt.%) | Ti (wt.%) | Others (wt.%) | UTS (MPa) |
|---------|-----------|-----------|-----------|---------------|-----------|
| 1 | 96.74 | 2.06 | 0.88 | 0.32 | 102.76 |
| 2 | 94.71 | 4.04 | 0.93 | 0.32 | 194.24 |
| 3 | 92.51 | 6.15 | 1.02 | 0.32 | 178.64 |
| 4 | 90.47 | 8.27 | 0.94 | 0.32 | 170.28 |
| 5 | 88.35 | 10.26 | 1.07 | 0.32 | 164.88 |
| 6 | 86.94 | 11.73 | 1.01 | 0.32 | 123.43 |
| 7 | 84.17 | 14.60 | 0.91 | 0.32 | 121.87 |
| 8 | 95.34 | 2.27 | 2.07 | 0.32 | 154.07 |
| 9 | 93.69 | 3.98 | 2.01 | 0.32 | 205.04 |
| 10 | 92.06 | 5.79 | 1.83 | 0.32 | 182.16 |
| 11 | 89.13 | 8.59 | 1.96 | 0.32 | 150.36 |
| 12 | 87.55 | 10.35 | 1.78 | 0.32 | 129.20 |
| 13 | 84.90 | 12.65 | 2.13 | 0.32 | 113.26 |
| 14 | 83.34 | 14.32 | 2.02 | 0.32 | 99.14 |
| 15 | 94.97 | 2.01 | 2.70 | 0.32 | 124.22 |
| 16 | 92.22 | 4.49 | 2.97 | 0.32 | 169.84 |
| 17 | 90.54 | 6.09 | 3.05 | 0.32 | 163.97 |
| 18 | 88.05 | 8.84 | 2.79 | 0.32 | 142.15 |
| 19 | 86.23 | 10.27 | 3.18 | 0.32 | 160.62 |
| 20 | 83.81 | 12.89 | 2.98 | 0.32 | 90.66 |
| 21 | 82.43 | 14.18 | 3.07 | 0.32 | 93.10 |

Mg and Ti ratios in the alloys change 2, 4, 6, 8, 10, 12, 14, and 1, 2, 3 wt.%, respectively. The others in Table 1 contain Mn (max 0.03%), Fe (max 0.1%), Cr (max 0.01%), Cu (max 0.05%), Si (max 0.1%), Zn (max 0.02%) and Ag (max 0.01%). Three tensile test bars are prepared according to the ASTM E9-09 standards [9]. Tensile tests are carried out by a computer-controlled SHIMADZU AG-X test machine at a strain rate of 1 mm/min and at room temperature. The results are obtained by getting the average of three testing specimens.

2.3.ANN

NNs are formed by various neurons which are organized in distinct layers. These layers are linked through the sliding weights. Fig. 1 shows basic elements of an artificial neuron.

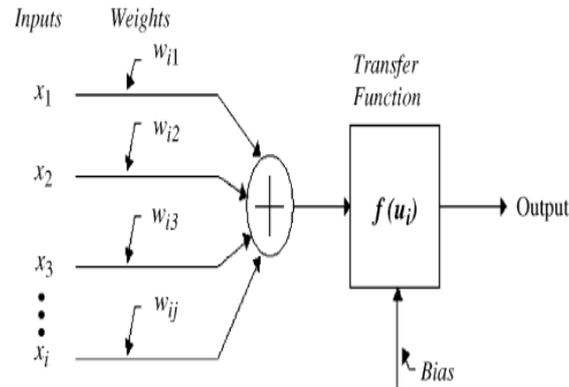


Fig. 1: Basic elements of an artificial neuron.

Neurons, in NN is an information processing method, are connected to each other and they are called as processing elements. Each neuron obtains the inputs with a weight and then each input multiplied by the corresponding weight. During the training process, these weights are calculated by an iterative technique. The network is performed with training data, input and output values. A back propagation (BP) neural network is a supervised learning method. In the training set, output values are produced from output nodes through the network. Then, these values compared to target values and after the error values are calculated [10, 11]. Sigmoid function used in ANN is the most common activation function. It joins curvilinear behavior, nearly linear and constant behaviors depending on the input value. The function takes a input value and returns a output bordered between [0,1]. NNs are usually categorized by their network topology and learning algorithms. BP algorithm is the most widely used training algorithm due to its simplicity and applicability [12, 13]. The inputs and outputs in ANN must be numeric and range the closed interval [0,1]. The normalization technique is used in the proposed ANN because of this conversion method according to the following formula:

$$\text{normalized value} = \frac{\text{input value} - \text{min value}}{\text{max value} - \text{min value}} \quad (1)$$

Output values are also in the range [0,1] and converted to its equivalent values based on reverse method of normalization technique [14].

In this present study, BP algorithm is used with a single hidden layer improved with training function called Trainlm. NN toolbox in Matlab is used to train and test the ANN. The training parameters used in this investigation are listed in Table 2.

Table 2: Training data in ANN

| | |
|--|------------------|
| Network Configuration | 3-5-1 |
| Hidden layer number | 1 |
| Hidden neuron number | 5 |
| The used transfer function | Logsig (sigmoid) |
| The used pattern number for training | 70% |
| The used pattern number for testing | 15% |
| The used pattern number for validation | 15% |
| Epoch number | 100 |
| Factor of learning | 0.01 |
| Factor of Momentum | 0.9 |
| Function of Training | Trainlm |
| Max_fail | 30 |

Different neuron numbers in the hidden layer are considered to find an optimal architecture. In the training, increased of neuron numbers (3–10) in a hidden layer are used to describe the output accurately. First layer of ANN is Al, Mg and Ti ratios as wt.% and outer layer is for the tensile strength of Al-Mg-Ti alloys. Experiment no: 5, 7, 9, 11, 13 and 16 are selected for testing test, remaining is selected for training test. After successful training, NN described in this work is used to examine and predict the tensile strength of the alloys.

3.Results and Discussion

It is clear from Table 1, the maximum ultimate tensile strength is observed with additions of 4 wt.% Mg and 2 wt.% Ti. The main reason for this improvement may be because of the reduced grain size and solid solution strengthening processes. The increasing of Mg and Ti contents did positively not affect the UTS of the alloys. This can be attributed to the increase in porosity and hard particle formation in the matrix. Feed forward back propagation neural network and sigmoid activation function as the transfer function are used in training of ANN. A total dataset of 21 samples are used, 70 % and 30 % of data's are used in the training and testing stages of the model. Fig. 2 shows train input and output, test input and output values.

It can be observed from the training test results (Fig. 2a) that the input and output values are very close and follow almost the same trend. The maximum and minimum errors for training test are observed on experiment no:19 (8.75%). and 20 (-11%), respectively. The linear correlation values for training pattern are found to be 0.9912%. Namely, prediction accuracy is 99.12 % for train test. The maximum and minimum errors for testing test are observed on experiment no:13 (15%). and 9 (-14%), respectively. The mean squared error (MSE), normalized MSE (NMSE), mean absolute error (MAE), minimum and maximum absolute errors for testing test is observed to be 0.0143, 0.3103, 0.0936, 0.0344 and 0.2223, respectively. Lower MSE values are better. Zero means no error. It is observed that ANN has enough accuracy in prediction of tensile strength of Al-Mg-Ti alloys with 91.88 % correlation. This relation has also shown in Fig. 2b. It can be stated that prediction accuracy for the testing set is 91.88 %. The values in the training stage are very close and error values for testing set is much greater compared to training set. The accuracy of testing set can be increased by changing the selected data and percentage of sets.

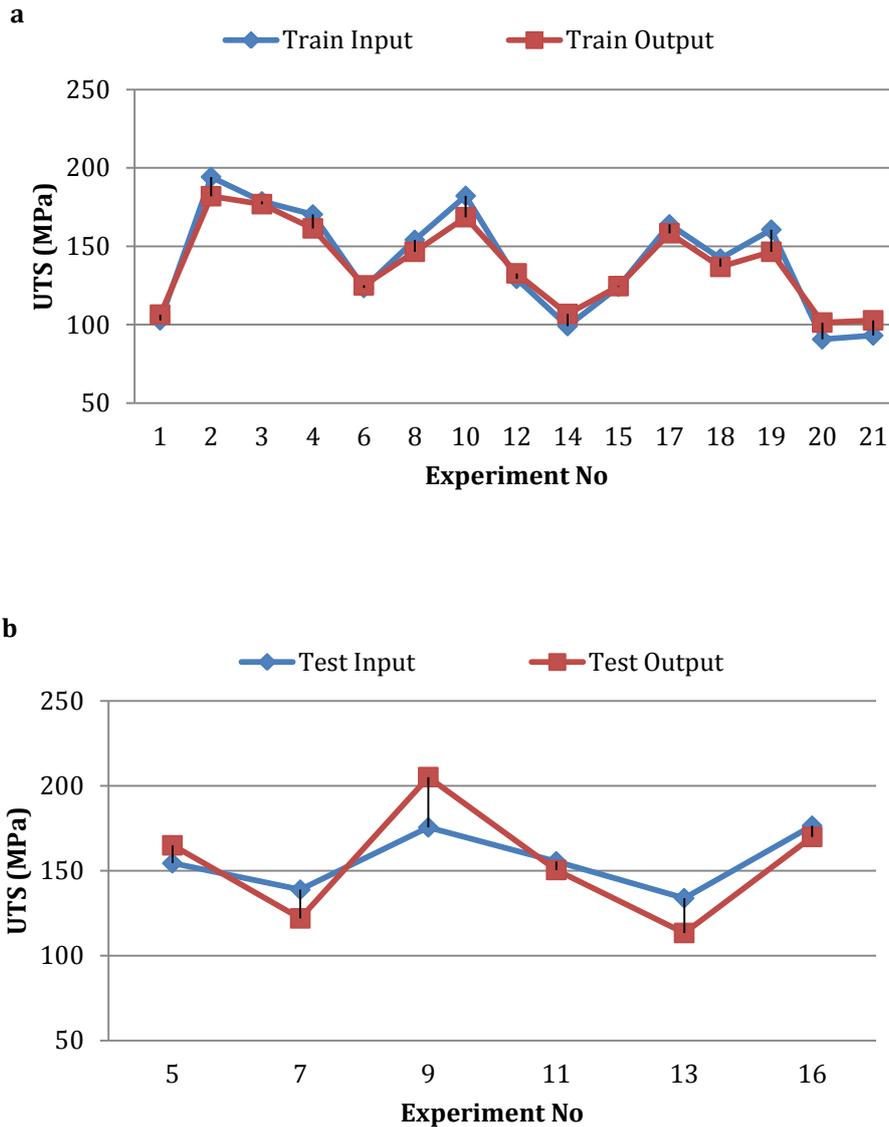


Fig. 2: Test results of input and output values of: (a) Train set (b) Test set

Fixing of the performance of the ANN model is very important. So, the used data are separated into two sets: the training and validating sets. These parameters of the network are calculated using the training set. When reaching the error goal the learning process is stopped and the network is evaluated with the data from the validating set [12]. In this study, the training and validating values are observed to be 0.99696 and 1.0, respectively. The error behavior of NN has to be observed to fix the results with minimum errors. There is no known formula to specify the number of neurons in the hidden layer. The number of neuron in the hidden layer can be identified experimentally [15]. It is seen that the proposed model with five neurons in a hidden layer has the smallest error value in the work. Fig. 3 shows the sensitivity of input vectors.

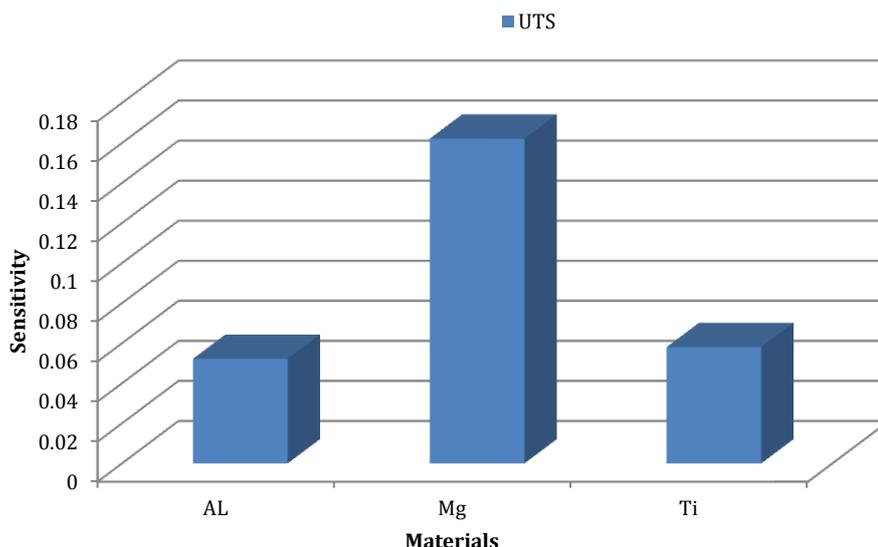


Fig. 3: Sensitivity of the materials on tensile strength

The influences of input parameters from minimum to maximum are examined by making the sensitivity analysis. The sensitivity of Mg (wt.%) vector is 0.1622 compared to 0.0580 for Ti and 0.0522 for Al (wt.%) vector. This means that any change in Mg level will have moderately more effective action on the network outputs (UTS values) than that result from changing Ti and Al levels.

4. Conclusions

The optimum values of Mg and Ti in alloys are 4 wt.% and 2 wt.%, respectively, for this study. The developed neural network can be used to predict the tensile strength of aluminum alloys with Mg and Ti for the given different composition rates. The prediction of ANN model is found to be in good agreement with experimental data. Linear correlation values for training and testing is 99.12% and 91.88% respectively. Among training parameters, it is found that the best training algorithm for the selected ANN is observed with five neurons in one hidden layer. It can be said that ANN is a successful analytical tool provided it is properly used and could be obtained by using neural network model the considerable savings in terms of cost and time.

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