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THEORETICAL ANALYSIS OF THE DUCTILITY, POROSITY, HARDNESS AND DENSITY IN ALUMINUM–MAGNESIUM ALLOYS WITH TITANIUM

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ABSTRACT

In the current study, aluminum-magnesium-titanium alloys were manufactured with sand casting method and the effects of titanium and magnesium on the ductility, porosity, hardness and density of these alloys were investigated. The influences of these elements were also studied using multi-layer perceptron neural network approach. Regression models were advanced to check both the performance and the reliability of the proposed neural network model. It was seen that linear correlation of all output values is highest than 90%. It was also observed that Mg has a greater effect than Al and Ti on the hardness and porosity values, whereas Al has more sensitivity on the ductility of alloys.

Keywords: Al alloys, Casting, Porosity, Hardness, Ductility, Density

ALÜMİNYUM-MAGNEZYUM-TİTANYUM ALAŞIMLARINDA SÜNEKLİK, POROZİTE, SERTLİK VE YOĞUNLUĞUN TEORİKAL ANALİZİ

ÖZET

Bu çalışmada, kum döküm yöntemiyle üretilen alüminyum-magnezyum-titanyum alaşımlarının süneklik, porozite, sertlik ve yoğunluk değerlerine magnezyum ve titanium elementlerinin etkileri çok katmanlı yapay sinir ağları yaklaşımı kullanılarak araştırılmıştır. Önerilen modelin güvenirliği ve performansı ilişkilendirme modeli kullanılarak kontrol edilmiş ve bütün çıkış değerlerinin liner korelasyonunun %90'dan daha büyük olduğu görülmüştür. Sertlik ve porozite oluşumunda magnezyumun, süneklik değerinde ise alüminyumun daha büyük etkiye sahip olduğu tespit edilmiştir.

Keywords: Al alaşımı, Döküm, Porozite, Sertlik, Süneklik, Yoğunluk

1. INTRODUCTION

Aluminum (Al) and its alloys are widely used in engineering structures and components where corrosion resistance or light weight is required because Al as lightweight material is considered as an exciting alternative material to reduce emission of greenhouse gases and improving fuel efficiency in the transportation sector [1-3]. Magnesium (Mg) with very low density of 1.74g/cm^3 decreases the density of Al alloys and increases the properties of these alloys to a degree. So, Al-Mg alloys are lighter than other aluminum alloys. Al-Mg based alloys are commonly used in wide variety of applications in industry such as shipbuilding and transportation [4, 5]. Although the cast-ability and strength of Al-Mg are improved by Mg addition to a certain extent, the presence of β-Al_3Mg_2 brittle phase reduces its toughness, corrosion resistance and formability [6, 7]. The mechanical behaviors of alloys can be improved by adding an element in the composition [8]. In addition, the morphology and distribution of intermetallics seen in microstructure and grain size and shape can be affected the mechanical and physical properties of alloys [9].

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In this study, Al alloys with different weight ratios of Mg and titanium (Ti) were procured by sand casting method and the effect of additions of Mg and Ti (different wt. %) on the determined properties of the as-cast Al-Mg-Ti alloys was investigated. Next, all results are examined and analyzed by numerical method using neural network (NN) which is a non-linear statistical analysis method. In the current work the MLP neural network approach was used to investigate the ductility, porosity, hardness and density of Al-Mg-Ti alloys. The main aim of this work is to study the obtained results by using this technique and to evaluate the accuracy of the proposed model.

2. MATERIALS AND METHODS

2.1. Materials

The alloys used for this work were produced by sand casting method, with the basic components of Al 99.70 wt.%, Mg 99.70 wt.% and titanium tablet (75% pure titanium and 25% flux).

2.2. Methods

Al was first heated up to 750ºC in an electro-resistance furnace into SiC crucible. Then, measured amount of the additives of Mg and Ti were added into the molten aluminum, respectively. Next, the melt was poured into the sand mould. The manufactured specimens have 18 mm diameter and 500 mm height. Later, the casted specimens were machined by using computer numerical control (CNC) machine to obtain samples. The melt was stirred and degassed by N_2 to avoid contamination and oxidation of molten aluminum and additives. The ductility, porosity, hardness and density values of the alloys were examined. The compositions and the ductility, porosity, hardness and density of the alloys were shown in Table 1. 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%) [10, 11]. The composition values given in table 1 were obtained using electron dispersive spectrum (EDS) method.

Table 1. Compositions, ductility, porosity, hardness and density values of the alloys

Exp. No	AL (wt.%)	Mg (wt.%)	Ti (wt.%)	Others (%)	Elongation (%)	Porosity (%)	Hardness (HBN)	Density (g/cm^3)	Partition
1	96.74	2.06	0.88	0.32	4.62	7.5	53	2.632	Training
2	94.71	4.04	0.93	0.32	16.19	9.3	63	2.595	Training
3	92.51	6.15	1.02	0.32	11.26	12.3	72	2.545	Testing
4	90.47	8.27	0.94	0.32	4.37	13.7	75	2.509	Training
5	88.35	10.26	1.07	0.32	2.79	14.4	92	2.484	Training
6	86.94	11.73	1.01	0.32	1.68	15.8	97	2.455	Training
7	84.17	14.6	0.91	0.32	1.25	16	100	2.422	Testing
8	95.34	2.27	2.07	0.32	11.19	5.9	54	2.667	Training
9	93.69	3.98	2.01	0.32	14.75	6.5	70	2.643	Training
10	92.06	5.79	1.83	0.32	6.79	8.2	74	2.605	Training
11	89.13	8.59	1.96	0.32	4.67	8.3	93	2.578	Testing
12	87.55	10.35	1.78	0.32	1.94	10.5	95	2.535	Training
13	84.9	12.65	2.13	0.32	1.08	11.1	109	2.512	Training
14	83.34	14.32	2.02	0.32	1.04	12.7	114	2.477	Training
15	94.97	2.01	2.7	0.32	7.98	2.6	57	2.714	Testing
16	92.22	4.49	2.97	0.32	4.48	5.3	72	2.667	Testing
17	90.54	6.09	3.05	0.32	2.95	7.8	80	2.628	Training
18	88.05	8.84	2.79	0.32	3.22	9.4	97	2.579	Training
19	86.23	10.27	3.18	0.32	3.01	9.8	100	2.568	Testing
20	83.81	12.89	2.98	0.32	0.79	11.9	110	2.518	Training
21	82.43	14.18	3.07	0.32	1.38	12.3	125	2.502	Training

The hardness analysis of the as-cast alloys was measured by using a Matsuzawa DXT-3 device (Rockwell superficial Hardness Scale HR 15 T with a diamond spot anvil and with total test force 147 N) according to the ASTM E18-11 standard [12]. The hardness results were transformed into Brinell scale.The density measurements were carried out on the alloy samples using the Archimedes water immersion method according to the ASTM C693-93 standard [13].

The size and distribution of porosity in a cast alloys plays an important role in controlling the mechanical properties. Therefore, porosity levels must be kept to a minimum. The percent porosity was calculated from the measured density and theoretical density by the following equation:

$$\%P = 100\left(P_t - P_{exp}\right) \qquad (1)$$

where $\%P$ is the percent porosity, P_t is the theoretical density, P_{exp} is the measured density.

2.3. Overview of Neural Network Model

NNs are mathematical models composed of several neurons. These neurons are arranged in different layers and these layers are linked through the variable weights. Neurons, in NN is an information processing method, are connected to each other and they are called as processing elements. The network is performed with training data, input and output values. [14, 15]. 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. Depending on the value of the input; it joins curvilinear behavior, nearly linear and constant behaviors. NNs are usually categorized by their network topology and learning algorithms [16]. Layered feed-forward NN is used in multi-layer perceptron (MLP) neural network system. The architecture of the MLPs is described by non-linear PEs, the function generally smoothed by sigmoid, logistic or hyperbolic tangent functions [17, 18]. In this present work, MLP neural network algorithm is used with one hidden layer and training function called Trainlm. The used parameters in the investigation are listed in Table 2.

Table 2. ANN training data

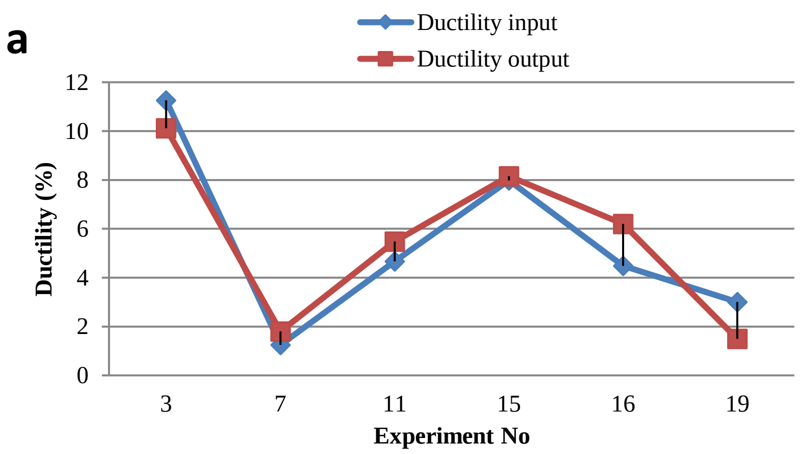
1	Network Configuration	3-4-4
2	Hidden layer numbers	1
3	Hidden neuron numbers	4
4	Used transfer function	Tangent
5	Used pattern numbers for training	70%
6	Used pattern numbers for testing	15%
7	Used pattern numbers for validation	15%
8	Epoch numbers	100
9	Training function	Trainlm

First layer of NN is corresponding to input values like Al, Mg and Ti. Outer layer of the NN is for the ductility, porosity, hardness and density values of Al-Mg-Ti alloys. Experiment no: 3, 7, 11, 15, 16 and 19 were selected for testing test, remaining was selected for training test. After successful training, NN described in this work was used to the ductility, porosity, hardness and density values. Statistical methods are used to compare the results produced by the network.

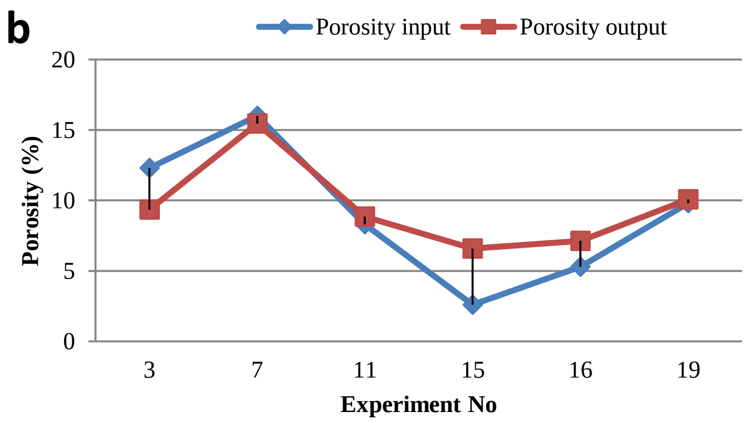
3. RESULTS AND DISCUSSION

The artificial neural network (ANN) was trained and implemented using MLP back propagation NN. Three input nodes arey Al (wt.%) Mg (wt.%) and Ti (wt.%), one hidden layer with four neurons and four output neurons are the ductility, porosity, hardness and density. 21 dataset are used to learn the proposed ANN. 70 % of data are used to train and remaining are used to test the model.

Fig. 1 shows input and output values of the ductility, porosity, hardness and density. It can be observed that there is a close relation between input and output values. The maximum variation of the ductility, porosity, hardness and density for testing test were obtained on experiment no: 19, 3, 3, and 11. The minimum variation of the ductility, porosity, hardness and density for testing test were obtained on experiment no: 16, 15, 7, and 7, respectively. Statistical parameters of testing set of NN model are presented in Table 3. The mean squared error (MSE) was 1.2607 for ductility, 4.7753 for porosity, 37.1033 for hardness and 0.0010 for density. The normalized MSE (NMSE) was 0.1158 for ductility, 0.2477 for porosity, 0.1397 for hardness and 0.1242 for density. The mean absolute error (MAE) was 0.9876 for ductility, 1.6924 for porosity, 5.7981 for hardness and 0.0278 for density. The minimum and maximum absolute errors were 0.1787 and 1.7176 for ductility, 0.2822 and 3.9883 for porosity, 2.4553 and 8.2455 for hardness, 0.0050 and 0.0590 for density. However, these error levels are satisfactory and smaller than errors that normally arise due to experimental variation. Linear correlation values of all parameters are higher than 0.90. Namely, prediction accuracy is 94.08% for ductility, 91.09% for porosity, 95.21% hardness and 97.28% for density. It was seen that the highest prediction accuracy carried out on density.

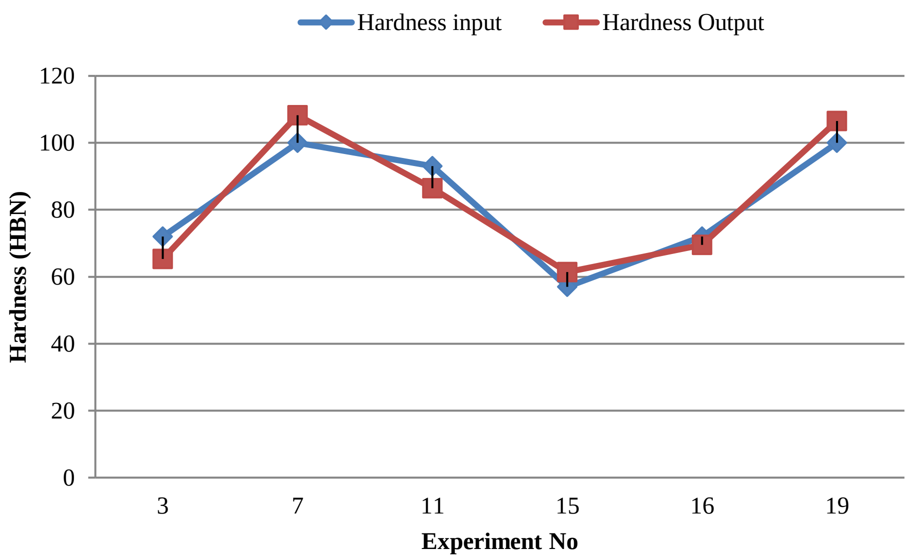


(a)



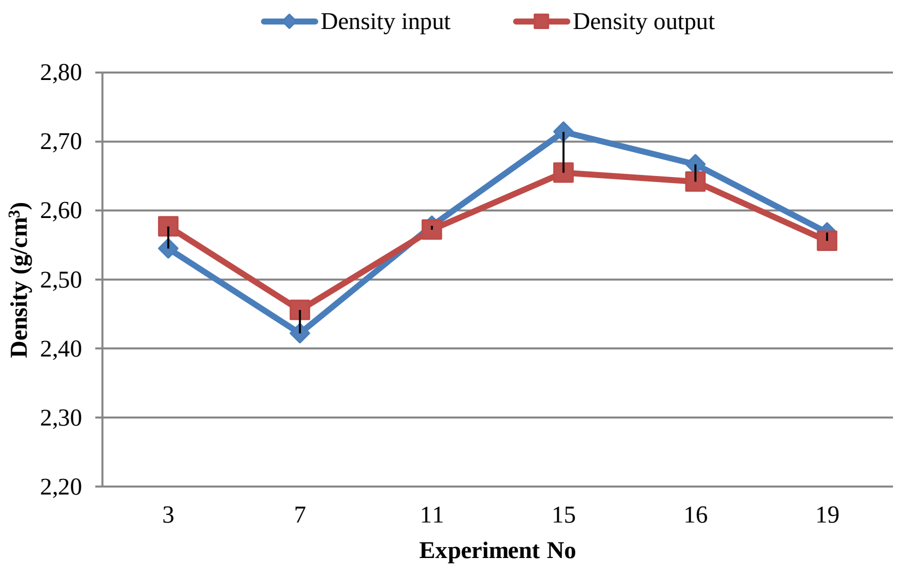
(b)

c



(c)

d



(d)

Figure 1. Input and output values of: (a) ductility, (b) porosity, (c) hardness, (d) density

Table 3. Statistical parameters of testing set

Performance	Ductility	Porosity	Hardness	Density
MSE	1.2607	4.7753	37.1033	0.0010
NMSE	0.1158	0.2477	0.1397	0.1242
MAE	0.9876	1.6924	5.7981	0.0278
Min. AE	0.1787	0.2822	2.4553	0.0050
Max. AE	1.7176	3.9883	8.2455	0.0590
Linear Correlation	0.9408	0.9109	0.9521	0.9728

The performance of the proposed ANN model is fixed by separating the data into two sets: the training set and the validating set. The 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 [19]. In this study, the training and validating values were observed to be 99% and 99%, respectively. MSE and the validation of training test are 0.0023 and 0.99, respectively. Lower MSE values are better. Zero means no error. Training part has much more accurate prediction as it is expected from the results where value of error is much greater for testing part. To change the percentages of partitions and the data selected as testing can improve the results and more accurate results can be gained for testing part. 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 [20] . It was seen that the ANN with four neurons in a hidden layer has the smallest error value in the work.

Fig. 2 shows the sensitivity values of input variables. This sensitivity analysis investigates the influence of input variables from minimum to maximum. The sensitivity of Al, Mg and Ti (wt.%) vector on ductility, porosity, hardness and density is 1.9813, 0.6269, 1.4181, 0.5264 and 0.8339, 0.7630, 2.7728, 0.5187 and 1.3586, 0.5855, 0.9545, 0.5190, respectively. Any change in Mg level will be affected the network outputs (hardness and porosity values) compared to Ti and Al levels. Additionally, the ductility more affects any change in Al level compared to changing Ti and Mg levels whereas the density more affect from Ti level.

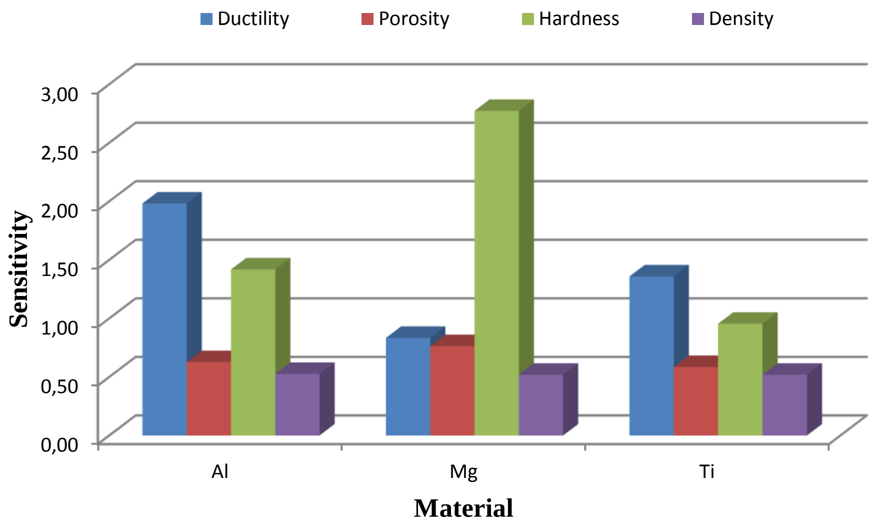


Figure. 2. Sensitivity of the materials on ductility, porosity, hardness, density

4. CONCLUSION

The using of ANN in calculating hardness and some properties for aluminum–magnesium-based alloys has been investigated. The developed neural network can be used to predict the ductility, porosity, hardness and density of aluminum alloys with Mg and Ti for he given different composition rates. The prediction of ANN model was found to be in good agreement with experimental data. Linear correlation value for training test is 99%. The lower and higher error rates were seen on density and hardness among all output parameters, respectively. Prediction accuracy for all network values is higher than 90%. It was found that the best training algorithm for proposed ANN model is that four neurons in one hidden layer. Therefore, in order to reduce testing time and cost satisfactory results can be estimated by using ANN values.

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