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Use of artificial neural networks for prediction of mechanical properties of Al-Si alloys synthesized by stir casting

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Abstract

Mechanical testing plays an important role in evaluating the fundamental properties of engineering materials as well as, in developing new materials. The use of conventional mathematical models in analytical calculating of the mechanical properties in most materials is very complex. In the current study Al-Si alloys were synthesized using the stir casting method. The mechanical properties as the tensile strength, Brinell hardness and wear property for the produced Al-Si alloys were investigated. Then, the obtained experimental results were used to train the artificial neural network (ANN). The neural network model is used to predict the effect of silicon content on the tensile strength, the hardness test, and wear loss for the prepared Al-Si alloys. Three neural networks were used in this study and the percent of silicon content variable was used as the ANN's input for each. Tensile test is used as ANN's output and the training function used is (traincgp) in first neural network. Also, hardness test is used as ANN's output and the training function used is (traincgf) in second neural network and wear loss test is used as ANN's output and the training function used is (traincgf) in third neural network. The obtained outcomes showed that predictions data in the applied neural networks were closer to the experimental results. The optimum mean square error (MSE) for ANNs during the tensile test, the hardness test and the wear loss test equal to 0.0335, 0.0023, 0.014 respectively. And these results were satisfactory.

Keywords

ANN; Mechanical properties; Wear test; EDX; MSE

Introduction

Aluminium-Silicon alloys are widely used as cast alloys for industry due to their excellent casting properties, low specific weight, good wear resistance and corrosion resistance, and good weldability. The use of Al-Si alloys varies from household food components to transportation and aircraft parts for greater weight loss [1,2]. The low density, high specific stiffness, high temperature resistance, wear resistance and low thermal expansion coefficient of the Al-Si hypereutectic (about 14–25% Si) alloys are of great interest in the transport industry due to its ability to replace cast iron in automotive engine parts [1,3]. The effect of adding silicon on the mechanical properties of aluminium alloys, such as tensile strength and hardness, was investigated in previous works [4,5]. The results showed that the tensile strength and the hardness properties of Al-Si alloys increase with the increasing of silicon content [4,5]. In recent decades, new computational methods have been introduced in some areas of technology, including materials science. The neural network theory based on previously acquired data, that is called training set, which is used to test the success of the system by using test data. Artificial neural networks are increasingly being used to perform many tasks. The advantage of neural networks is their ability to learn and adapt for changing conditions, as well as their ability to generalize their knowledge. Due to these properties, ANN can be used in all cases; when the application of traditional methods encounters great difficulties, analytical solutions are impossible or difficult to achieve, and in tasks which requiring linking and processing incomplete or inaccurate information [6,7]. Artificial neural network results showed good agreement with experimental data, and ANN provided additional useful data from relatively small experimental databases. A very good performance of a trained neural network has been achieved [8]. The results obtained from the experimental tests and the results obtained by using neural networks were largely coincidence. The ANN model was used to help in predicting and optimizing the wear rates of composites. The results showed that ANN is an effective tool for the prediction of the properties of MMCs and is very useful instead of laborious experimental processes [9,10]. Artificial neural networks (ANN) have emerged as a new branch of computing, suitable for use in a wide range of areas. Numerous studies have been published on the prediction of properties of several composites [11, 12]. Several studies have been conducted to study the effectiveness of different learning algorithms for artificial neural networks (ANN) in finite-element method ''FEM'' modelling of Al-Si alloy as volume eutectic per-cent, silicon volume per-cent, distance between silicon rods and average length of silicon rods [13,14]. The training of ANNs by back propagation involves the feed forward of the input training pattern, the calculation and back propagation of the associated error and the adjustment of weights. Multilayer perceptron (MLP) is a feed forward of the Artificial Neural Network model that maps sets of input data into a set of appropriate outputs. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one except for the input nodes; each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable [15]. A general view of the MLP network which applied in the present work is displayed in Figure 1.

In the present work, the neural network model is used to predict the effect of silicon content on the hardness, tensile strength, and wear loss test for the prepared Al-Si alloys and hence reducing the number of experiments, time, and consequently the costs. The neural network was modelled in the Matlab software.

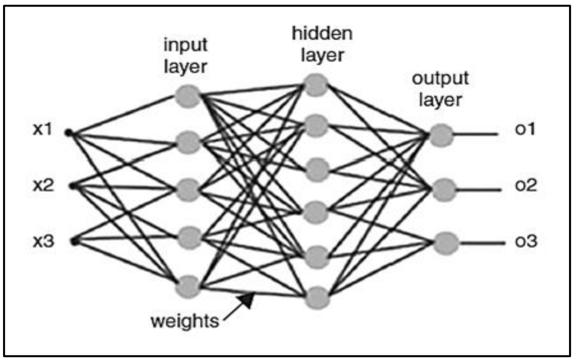

Figure 1 General view of the MLP network [15]

Materials and Methods

Al-Si alloy was synthesized by using the stir casting method which involves metal melting, stirring the molten metal, introducing the required particles and then let the resulted mixture to solidify. The materials used to prepare the alloy are; commercial aluminum (supplied by the aluminum company of Egypt, purity 99.7%, chemical analysis of Al as shown in Table1), Silicon with purity is 99.5%. The melting process was done in in a graphite crucible and put in a vertical muffle furnace at 720 ˚C. The molten bath in the crucible is stirred mechanically (400 rpm) for a certain time (20 min.), and poured the molten alloy into a steel mold. The samples were prepared with varying Si content in the range of (5, 7.27, 8.32, 10, and 11 %). Suitable cylindrical solid specimens were prepared for the microstructure examinations by polarized reflected light microscope (Model-OLYMPUS BX51, Japan) supplied with a digital camera (Leica DM500), and Energy Dispersive X-ray (EDX) mapping.

The mechanical properties of the produced alloys, as tensile strength, hardness and wear loss test were evaluated. Tensile strength test was performed using tensile test on (VH-F1000 kN) SHIMADZU micro-computer controlled electronic universal testing machine, with strain rate 5x10-3 s-1 and the specimens were prepared according to ASTM standard test method as shown in figure 2 (diameter was 10 mm and the gage length was 60 mm) [16]. The experimental results of the tensile tests for the Al-Si alloys were in the range (74, 78, 83, 88, 92 N/mm^2) for different Si contents. The hardness test has been done by using Hardness Brinell test and the specimens for this test were polished. The experimental hardness results of the Al-Si alloys were in the range (49, 52, 55, 58, 61 HB) for different Si contents. The wear test of the alloys measured using a pin-on-disk testing device. The weight loss of the specimens measured and calculated with respect to time, weight loss at constant load of 0.886 Kgf, at the same sliding speed of 250 rpm. Wear loss values were (2.42, 2.03, 1.83, 0.93, 0.37gm) for different Si contents.

Table 1 Chemical analysis of the aluminum

Element	%
Fe	0.059
Si	0.05
Mn	0.008
Mg	0.001
Na	0.0064
Ti	0.004
Ca	0.004
Al	balance

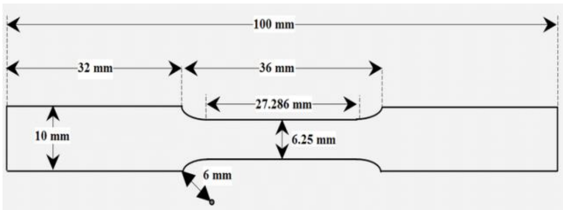

Figure 2 Dimensions of tensile specimen (in mm)

Designing and Training of Neural Networks

This work was accomplished by using the neural network toolbox available with MATLAB software.

Neural Network for Tensile test

The used ANNs architecture is shown in figure (3). The results of the experimental tensile test are used to train the artificial neural network (ANN). The variable of silicon content is used as ANN's inputs; tensile test is used as ANN's outputs. The used ANN consists of three layers; Input layer contains 1 neuron; the hidden layer contains 9 neurons, while the output layer contains 1 neuron; Conjugate Gradient with polake Ribiere Restart (traincgp) is used as the training function.

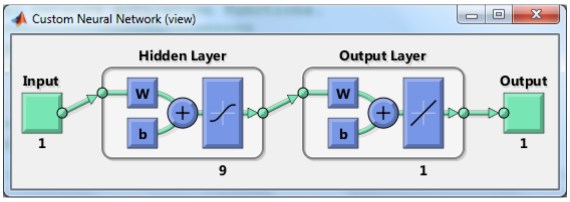

Figure 3 ANNs block diagram for tensile test, the hidden layer contains 9 neurons.

Neural Network for Hardness test (HB)

The used ANNs architecture is shown in figure (4). The results of the experimental hardness test are used to train the artificial neural network (ANN). The variable of silicon content is used as ANN's inputs; hardness test is used as ANN's outputs. The used ANN consists of three layers; Input layer contains1 neuron; the hidden layer contains 7 neurons, while the output layer contains 1 neuron; Conjugate Gradient Back propagation with Fletcher-Reves Restart (traincgf) is used as the training function.

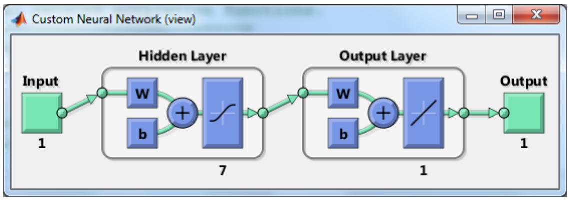

Figure 4 ANNs block diagram for hardness test, the hidden layer contains 7 neurons

Neural Network for Wear test

The used ANNs architecture is shown in figure (5). The results of the experimental wear test are used to train the artificial neural network (ANN). The variable of silicon content is used as ANN's inputs; wear test is used as ANN's outputs. The used ANN consists of three layers; Input layer contains 1 neuron; the hidden layer contains 5 neurons, while the output layer contains 1 neuron; Conjugate Gradient Back propagation with Fletcher-Reves Restart (traincgf) is used as the training function.

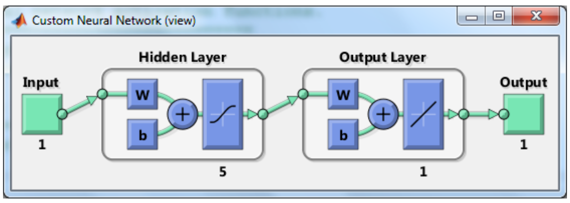

Figure 5 ANNs block diagram for wear test, the hidden layer contains 5 neurons

Results and Discussions

Al-Si alloy characterization

Figure 6 shows the microstructure of the produced Al-Si alloy, using light microscope, resulting coarse microstructure in which the eutectic composition comprises large plates or needles of silicon (dark grey) in a continuous aluminium matrix (light). Figure 7 shows Energy Dispersive X-ray (EDX) mapping of Al-Si alloy. The figure shows that the produced alloy microstructure displays a homogeneous distribution of silicon in the Al matrix. The eutectic composition is composed of individual cells within which the silicon particles appear to be interconnected. Alloys having this coarse eutectic composition exhibit low ductility due to the brittle nature of the large silicon plates

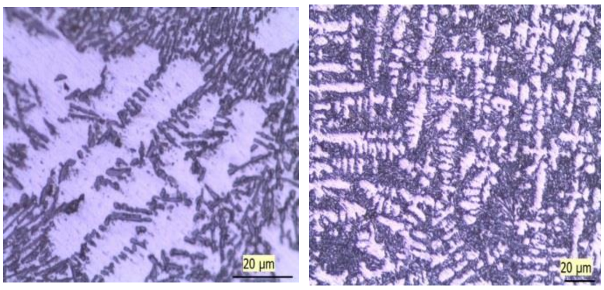

Figure 6 The microstructure of the produced Al-Si alloy, using light microscopy, X=10 and X=100

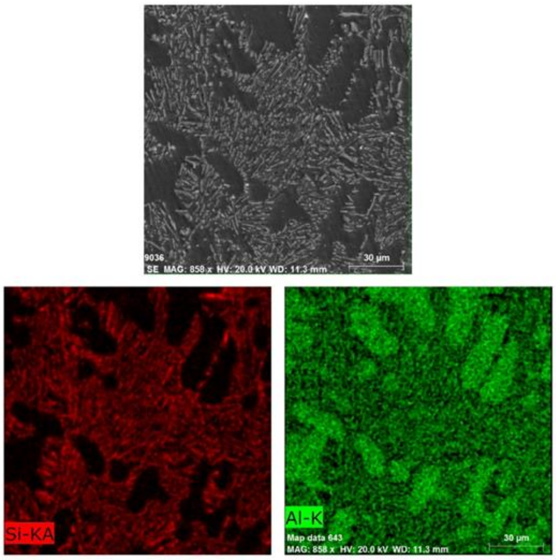

Figure 7 EDX mapping of Al - Si alloy

Prediction of mechanical properties by ANN

ANN is applied to predict the effect of silicon content on the hardness, tensile strength, and wear loss test for the prepared Al-Si alloys. A comparison identical between the results obtained from the experimental tests and the results obtained by using neural networks; the ANN model was applied to help in predicting the properties and it is considered as an effective tool instead of laborious experimental processes. According to the most minimum error (in terms of MSE) values which are obtained at the end of learning process, mean square error (MSE) is a good scale to have data about the performance of learning. The experimental results and ANN's predictions are compared and mean square error (MSE) is computed using equations (1) and (2) [17].

$$e_k(n) = d_k(n) - y_k(n), \quad (1)$$

$$\varepsilon_{av} = \frac{1}{2N} \sum_{n=1}^{N} \sum_{k \in c} e_k^2(n) \quad (2)$$

Where,

N is the total number of samples, and

C is all the neurons in the output layer

The learning process is repeated till the error is satisfied. The used method was applied for all the information in the training data. Finally, the method used the test data to confirm the non-linear relationship between the sets of inputs and outputs [17]. Multi-layered neural networks architecture and parameters of training for all examined cases are shown in table 2

Table 2 - MLP structure and learning parameters

	ANN (Tensile strength)	ANN (Hardness HB)	ANN (Wear loss)
Num. of neurons in input layer	1		
Num. of neurons in hidden layer	9	7	5
Num. of neurons in output layer	1		
Training algorithms	traincgp	traincgf	traincgf
The initial weights and biases	Set Randomly by Mat Lab in range [−1, 1]		
Activation functions for hidden layer	Log sigmoid		
Activation functions for output layer	Pure line		
Num. of epochs	1000		
Error goal	1e-7		
MSE	0.0335	0.0023	0.014

Prediction of Tensile test by (ANN)

Tensile test is the most common procedure; hence, it is an easy way to get information about the strength of materials and deformation properties in a single test. Figure 8 shows that the tensile strength increases from 74 to 92 N/mm^2 by increasing the silicon content from 5 to 11%. This effect of silicon is attributed to the size, shape and distribution of silicon particles in the cast structures, which agrees with previous works [3, 4]. As well as, it is clearly from figure 8 that the experimental and predicted values obtained from ANN are very close to each other. The superior performance of the trained NN can be indicated by MSE criteria, agree with [15,18] where MSE= 0.0335

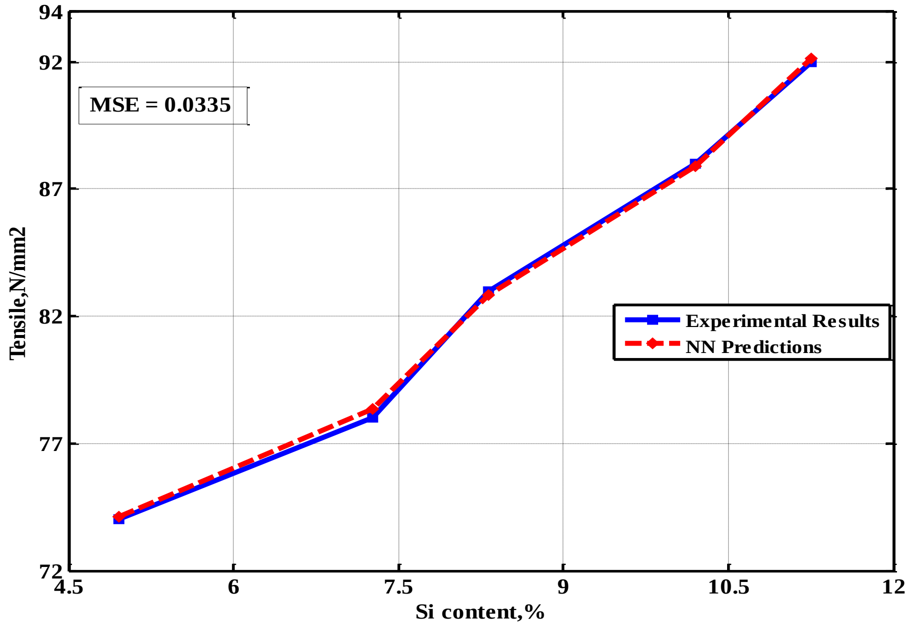

Figure 8 Experimental and predicted results of the Si content % effect on the tensile test of Al-Si alloy

Prediction of Hardness test

Figure 9 shows the relation between Si content percent versus predicted values of hardness test in comparison with the experimental results. The hardness test increases from 49 to 61 HB by increasing the silicon content from 5 to 11%. The Silicon effect is due to the size, shape and distribution of silicon particles in the cast structures [3, 4]. As well it is clearly seen from figure 9 that the NN predictions coincide with the experimental results. The superior performance of the trained NN can be indicated by MSE criteria, agree with [15,18] where MSE = 0.0023

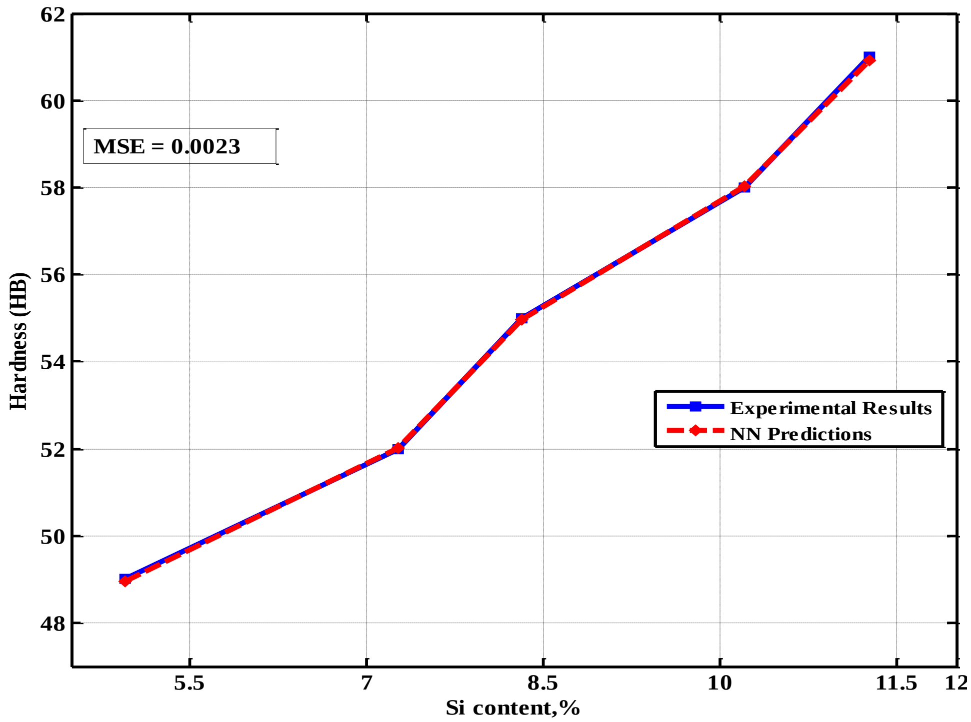

Figure 9 Experimental and predicted results of the Si content % effect on the hardness test of Al-Si alloy

Prediction of Wear loss test

Figure 10 shows the relation between the wear loss and silicon content % of Al-Si alloys. The results showed that the wear weight loss decreases from 2.43 to 0.37gm as the silicon contents increases from 5-11%. This effect of silicon is attributed to the size, shape and distribution of silicon particles in the cast structures, which are confirmed by

[19, 20]. Also figure 10 shows the relation between Si content percent versus predicted values of wear loss test in comparison with the experimental results. It is clearly seen from figure 10 that the experimental and predicted values obtained from ANN are very close to each other. The superior performance of the trained NN can be indicated by MSE criteria, agree with [15, 18] where MSE = 0.014

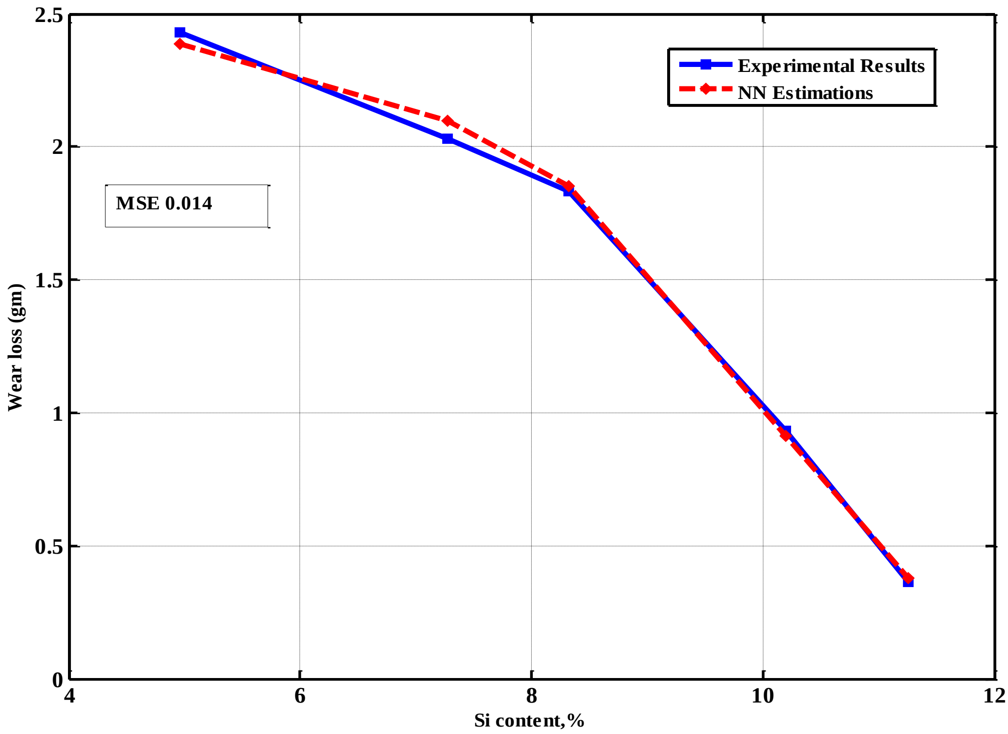

Figure 10 Experimental and predicted results of the Si content % effect on the wear loss of Al-Si alloy

Conclusions

In the present study, the predictions of mechanical properties under variable of silicon content % are performed. The following conclusions are obtained:

1. Artificial Neural Network (ANN) can be used as an efficient tool in predicting mechanical properties
2. Under the studied conditions and utilized materials, predicted values of mechanical properties of Al-Si alloys by ANN can be used by designers and process engineers to save costs, efforts time, materials and items of the experiment.
3. Experimental tensile, hardness and wear test of specimens have shown a consistency and good agreement with predicted results of ANNs model.
4. The designed ANN model predicted the tensile test with MSE is 0.0335, hardness test with MSE is 0.0023 and wear loss test with MSE is 0.014.

References

[1] J.E. Gruzleski, B.M. Closset, The treatment of liquid aluminum-silicon alloys, American Foundry men's society, (1999) 1-256

[2] M.N. Efzan, H.J.Kong and C.K.Kok , Review: Effect of Alloying Element on Al-Si Alloys, advanced materials research, 845, (2014) 333-359.

[3] Chaowalit Limmaneevichitr and Witthaya Eidhed, Effect of Flux Compositions on Grain Refinement in Al-Si-Mg Alloy, Light Metals, (2005) 1107-1110

[4] Milind G Kalhapure, Pradeep M Dighe, Impact of Silicon Content on Mechanical Properties of Aluminum Alloys, International Journal of Science and Research, 4, (2015) 38-40

[5] Mohammad reza Zamani, LorenzoMorini, LorellaCeschini, SalemSeifeddine, The Role of Transition Metal Additions on the Ambient and Elevated Temperature Properties of Al-Si Alloys Materials Science and Engineering: A, 693, (2017) 42-50

[6] A. Necat, K. Rasit, Use of artificial neural network for prediction of physical properties and tensile strengths in particle reinforced alüminum matrix composites, Journal of Materials Science, 40, (2005) 67-70

[7] S. Malinov, W. Sha, The neural network modeling of titanium alloy phase transformation and mechanical properties, the journal of the Minerals, Metals & Materials Society, 57, (2005) 54-5.

[8] Necat Altinkok. Use of Artificial Neural Network for Prediction of Mechanical Properties of a-Al2O3 Particulate-reinforced Al–Si10Mg Alloy Composites Prepared by using Stir Casting Process, Journal of composite materials, 40,(2006) 780-696

[9] Rashed, F. S., Mahmoud, T. S. Prediction of wear behaviour of A356/SiCp MMCs using neural network, Tribology International, 42, (2009) 642-648

[10] H.K. Durmus, E. Ozkaya, C. Meric,The use of neural networks for the prediction of wear loss and surface roughness of AA6351 aluminium alloy, Materials and Design, 27 (2006) 156–159

[11] Rajkovi c V, Bo zic D, Stasi c J, Dim ci c B. Properties of Cu–Al2O3 composites obtained by high energy milling and internal oxidation, Association of Metallurgical Engineers of Serbia, 15 (2009) 181–188

[12] Hussain Z, Keong KH. Studies on alumina dispersion strengthened copper composites through ball milling and mechanical alloying method, Jurnal Teknologi, 43, (2005) 1–10

[13] A. Mazahery and M.O. Shabani, Process conditions optimization in Al–Cu alloy matrix composites, Powder Technology, 225, (2012) 101-106

[14] M.O. Shabani and A. Mazahery, Artificial Intelligence in numerical modeling of nano sized ceramic particulates reinforced metal matrix composites, Applied Mathematical Modelling, 36 (2012) 55-65

[15] Mostafa Amirjan, Hamid Khorsand, Mohammad Hossein Siadati, Reza Eslami Farsani Artificial Neural Network prediction of Cu–Al2O3 composite properties prepared by powder metallurgy method, Journal materresttechnl, 4 (2 0 1 3) 351–355

[16] ASM Metal handbook, Mechanical testing American Society of metals, 8 (1985) 17-109

[17] Altinkok N, Koker R. Neural network approach to prediction of bending strength and hardening behavior of particulate reinforced (Al–Si–Mg)–aluminium matrix composites. Materials Design, 25 (2004) 595 - 602

[18] Mustafa Taskin, Halil Dikbas and Ugur Caligulu Artificial Neural Network (ANN) Aporoach to prediction of diffusion bonding behavior (shear strength) of Ni-Ti alloys manufactured by powder metallurgy method, Mathematical and Computational Applications, 13 (2008) 183-191

[19] H. Torabian, J.P. Pathak, and S.N. Tiwari, Wear Characteristics of Al-Si Alloys, Wear, 172 (1994) 49-58

[20] Lozano D E, Mercado-solis R D, Perez A J, Talamantes J, and Morales F. Tribological behaviour of cast hypereutectic Al–Si–Cu alloy subjected to sliding wear, Wear, 267 (2009) 545-549