NEW APPROACH IN PREDICTING ALUMINUM-ALLOY PROPERTIES USING NEURAL NETWORKS

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Abstract - In this study the impact of alloying elements on hardness, for different series of Aluminum alloys, was analyzed and studied using a mathematical modeling tool based on Artificial Neural Networks (ANN). This new model was developed as multi-layer feed forward network with a hidden layer that can approximate any complex function and back-propagation learning algorithm. Thus, it is possible by using this model to predict properties of Aluminum alloys, in particular hardness, based on certain punch of inputs. The latter includes the weight percentage of the compositioncontents of various metals such as Cr, Cu, Fe, Mg, Mn, Si, Ti, Zn, and the Aluminum.In the current research work, several runs were made using this newly developed model, and published results of previous experimental research, available in open literature.The obtained results here were found in full agreement with those reported by other researchers. Thus, it is deemed that such model could help researchers and industries in designing the desired Aluminum alloy and predicting its hardness at no cost. Equally important is relatively high accuracy of obtained results.

Keywords - Aluminum alloy, Alloying elements, hardness, Neural Networks.

I. INTRODUCTION

During last decades,Aluminum and its alloys are extensively used in different industries and wide spectrum of applications, including but not limited to aircrafts, automotive and transmission lines.This is due to the fact that Aluminum Alloys enjoy low density, good malleability and formability, high corrosion resistance and high electrical and thermal conductivity. Equally important are machinability and workability of aluminum alloys: it is much easierto form and machine alloys. However, pure Aluminum and its alloys still have some problems: mainly low strength and unstable mechanical properties. Some of mechanical properties, such as hardnessof Aluminum Alloys can be improved by (i) alloying, (ii) cold working and (iii) heat treatment[1]. Hardness which is a measure of a material to resist indentation and it is closely related to material strength [2].Researchers from different parts of the world have studied the development of new approaches, such as neural networks, to predict the chemical composition and cooling rate for Mg-Al-Zn cast alloys [The results of this investigation show that there is a good correlation between experimental and predicted dates and the neural network has a great potential in mechanical behaviour modelling of Mg-Al-Zn alloys. L.A. Dobrzański, M. Król(2010)investigated adding various reinforcements to the Aluminum matrix in order to improve mechanical properties such as strength and withstanding creep and fatigue conditions [2,3,4]. Another group of researchers, K.Mroczka, A.Wojcicka and P. Purtyka (2012), managed to produce a new alloy with high hardness of 146 HV10 after annealing for 48 hours at 160 C. Employing heat treatment (T5) by A. Shahsavaria,(2015) was found to improve hardness value and ultimate tensile strength, but with a decrease in ductility [5]. Hot extrusions experiments, by Malinova, and Tang&Pan (2004), for AZ31 and AZ61 magnesium alloys proved that Y (Yttrium) and Zn additionshas a significant influence on the mechanical properties of Mg-Zn-Zr-Y alloys [6, 7]. But in the previous theoretical studies, e.g. neural networks, it should be remembered that some error in predicting some of properties is inevitable. In the present research paper, a new and improved simulation model, based on neural networks and past experience was developed to predict the hardness of aluminum with magnesium alloys.Al-alloy, in particular 6061,is widely used in the automotive industry for the fabrication of main parts, such as pistons, cylinder head, wheels, panels and even in the structure [8,9]. Such improvement could be achieved through the addition of some of well-known alloying elements, cold working and heat treatment. Alloying elements are selected according to their effects and suitability. The alloying elements may be classified as major elements, minor elements, microstructure modifiers and impurities. However, the impurity elements in some alloys could be major elements in others[10]. In this paper the effect of alloying elements such as; Major elements (Si ,Cu ,Mg), Minor elements(Ni, Sn) ,Microstructure modifier elements(Ti, B, Sr ,Be ,Mn ,Cr) and Impurity elements(Fe, Zn) on hardness of Aluminum alloys are reviewed. Artificial neural network (ANN) technique was employed to predict the micro-hardness of AA6061 friction stir welded plates. Mean absolute percentage error (MAPE) for train and test data sets did not exceed 5.4% and 7.48%, respectively. Considering the accurate results and acceptable errors in the models' responses, the ANN method can be used to economize material and time [11]. GhetiyaN. D. and Patel K.M designed a back propagation neural network to predict the mechanical properties of friction stir welded aluminum alloy. Tool shoulder diameter, welding and rotational speed

and axial force were the parameters that their effect was investigated on the tensile strength of the weld[12] used neural networks and Fourier transforms for real time evaluation of friction-stir welding. Ali Bakara and George Panoutsosillustrated quality monitoring frame work for steel friction-stir welding using computational intelligence. A model is developed to correlate the relations between the hardness/impact strength with tool rotation and weld steel using neural networks[13]. The optimized process conditions arepredicted to improvise the impact strength and hardness of the weld. Further, the morphology of the weld is studied using SEM to know the material flow characteristics [14].

II. METHODOLOGY

In this research work, anew tailor-made model (software) was developed based on ANN to determining the relationship between alloying elements and hardness of heat treated aluminum alloys. The results of previous research work in this particular field were collected, reviewed and used in this newly model as a data base, i.e. library. These include but not limited to composition for different series of aluminum alloys and their mechanical properties. The input data for the investigated new alloy are basically percentages of alloying elements and aluminum, and hardness as the main output.The model evaluates the error values and then predicts the value of hardness in order to correct output of ANN system for the test data. The ANN software is employed here to analyze the input, collectedexperimental data, in order to predict the optimum hardness of the tested Aluminum alloys as a function of various contents of alloying elements.

III. DATA COLLECTION AND DATABASE CONSTRUCTION

The performance of an ANN model depends upon the data set used for its training. Therefore, for a reliable neural network model a significant amount of data as well as powerful computing resources are necessary. Some experimental data on mechanical properties of Aluminum alloys at different conditions are collected from the literature. Samples of these dates are shown in table 1.

The data were divided in proportions of 75% for the learning set and 25% for the validation set. It is recommended 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 an interval of 0.1-0.9 [9]. The later reference has used the following equation to calculate the normalized value as;

$$P_n = 0.1 + \frac{(0.9-0.8)\times(P-P_{min})}{P_{max}-P_{min}} \quad (1)$$

Where:Pn is the normalized value of P, which is of a maximum and a minimum valuegiven by P_{max} and P_{min}, respectively [9]. The collected data is designed for the formationof the mathematical model for the determining of hardness Vickers (HV) number taking into account the effects of alloying elements.

Table 1: Database

(HV)	Zn	Ti	Si	Mn	Mg	Fe	Cu	Cr	Al
118	0.15	0.15	0.5	1.2	0.2	0.7	3.9	0.1	93.05
155	0.25	0.15	1.2	1.1	0.8	0.7	5	0.1	90.65
118	0.25	0.15	0.8	1	0.8	0.7	4.5	0.1	91.65
137	0.25	0.15	0.5	0.9	1.4	0.5	4.1	0.1	92.05
149	0.25	0.15	0.5	0.9	1.7	0.5	4.55	0.1	91.3
137	0.25	0.15	0.5	0.9	1.3	0.5	3.95	0.1	92.3
124	0.25	0.15	0.5	0.9	1.2	0.5	3.8	0.1	92.55
146	0.25	0.15	0.5	0.9	1.6	0.5	4.4	0.1	91.55
146	0.25	0.15	0.5	0.9	1.5	0.5	4.25	0.1	91.8
155	0.25	0.15	0.5	0.9	1.8	0.5	4.9	0.1	90.85
137	0.25	0.15	0.2	0.9	1.2	0.5	3.8	0.1	92.85
146	0.25	0.15	0.2	0.9	1.8	0.3	4.9	0.1	91.35
92	0.1	0.1	0.5	0.1	0.75	0.35	0.1	0.1	97.85
80	0.1	0.1	0.45	0.1	0.7	0.35	0.1	0.1	97.95
107	0.1	0.1	0.55	0.1	0.8	0.35	0.1	0.1	97.75

the ANN Model

Neural networks are typically organized in layers. Layers are made up of a number ofinterconnected ‘nodes’ which contain an ‘activation function’. Patterns are presented tothe network via the input layers, which communicate to one or more hidden layers where the actual processing is done via a system of weighted connections. The hidden layers then link to an output layers where the output results are shown figure(1)Pattern recognition neural network (view).

Multi-layer feed forward network models with one hidden layer can approximate anycomplex nonlinear function provided that sufficient hidden layers of neurons are available.

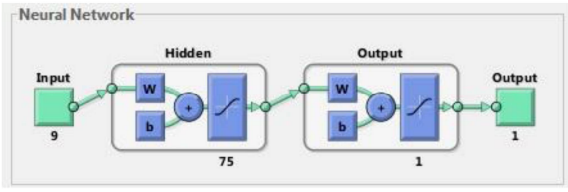


Fig.1 Pattern recognition neural network (view)

Therefore, in this study, multi-layer feed-forward network models, containing one hidden layer, were used. Determination of optimum number of the hidden layers of neurons is very important in order to predict, accurately, a parameter using ANNs. However, there isno theory yet that can states how many hidden layers of neurons are needed to be used for a particular problem.The best approach to find the optimum number of hidden neurons is to start with a fewnumbers of neurons and then slightly increase 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 avoid the training difficulties and balance the important of each parameter during training process, the examined data were normalized.

RESULTS AND DISCUSSIONS

Different pre-process parameters have important influences on the predicted results. Aneffort was made for improving the pre-processes of the ANN model. Model of neural network was used to verify the experimental mechanical properties such as Vickers hardness. Multi Layers were applied for calculations (Multi-Layer perceptron (MLP). The number of nodes in the input was represented by used alloying elements, while the output layer was defined as hardness.The Performance and evaluation of the neural network output were calculated. The performance is computed in the form of mean square error (MSE) as illustrated in equation (2).

$$mse = \frac{\frac{1}{2}\sum_{i=1}^{n}(t_i - o_i)^2}{N} \quad (2)$$

Where: t_i and o_i are the predicted and observed values of output respectively. In figures(2, 3, 4) the hardness values predicted by the model are compared with those ofexperimental results that were collected from the literature and shown in table (1). Figure (2)shows the best performance of the learning curve and output of the developed model. While figure (3), illustrates the regression between the model output (hardness number), and the target. In figure (4) the agreement between the predicted hardness values using the newly developed model and the actual experimental results for different Aluminum alloys. The values predicted by ANN are in very good agreement with those obtained experimentally as shown in table (2). The predicted and measured values of the hardness number indicate that this approach is useful in modeling the mechanical properties in heat treatment technique.The combination of Copper, Silicon, Magnesium, Manganese, and Zinc increase the hardness of Aluminum alloys.In this work the heat treatments, annealing temperature, aging temperature, and aging time were not included, which also have a good influence on mechanical properties.
0.375700557

Table 2: Actual and predicted value of hardness

actual		predicted		relative error
normalized		normalized		
0.672955975	137	0.681579271	138.3711	0.010008059
0.672955975	137	0.645438355	132.6247	0.031936508
0.389937107	92	0.375700557	89.73639	0.024604473
0.729559748	146	0.737767469	147.305	0.008938545
0.911949686	175	0.906012147	174.0559	0.005394678
0.358490566	87	0.369711234	88.78409	0.020506737

CONCLUSIONS

The following concluding remarks can be highlighted as main results of this theoretical study:

1. The mechanical properties of Aluminum alloys are strongly affected by the Alloyingelements and their concentration (wt%). It is found that as Si,Mn, Mg,Cu,Ti,Cr and Fe elements increased, the hardness will increase.
2. Results show that the improved model could apparently decrease the predictionerrorsand thus higher accuracy of the predicted results.
3. The predicted results were found to be in good agreement with those obtained experimentally.

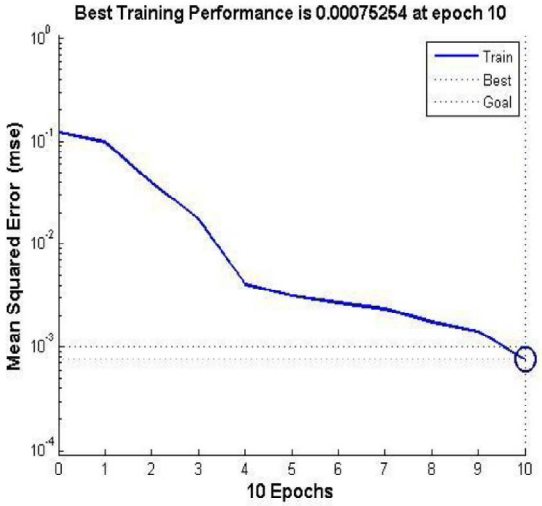


Fig 2: Performance (learning curve) of neural network

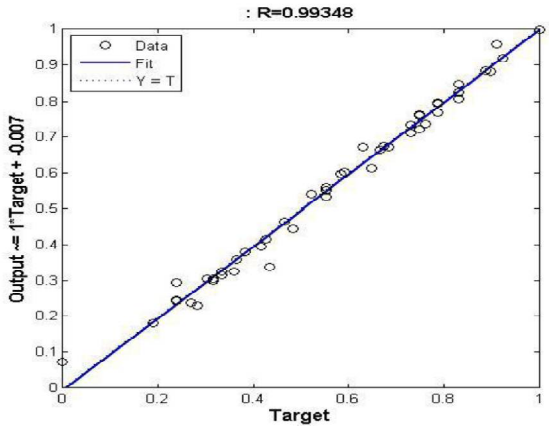


Fig 3: Regression

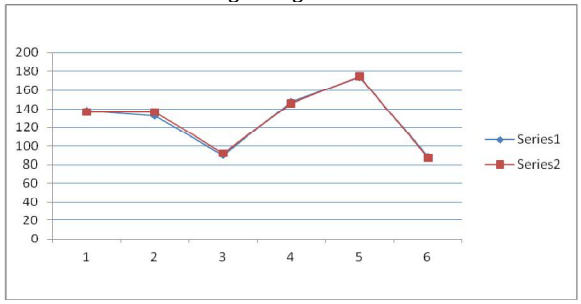


Fig 4: The relationship between actual (1) and the predicted (2) values of hardness HV.

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