J MATER RES TECHNOL. 2013;2(4):351–355

Available online at www.sciencedirect.com

jmr&t Journal of Materials Research and Technology

www.jmrt.com.br

Original Article

Artificial Neural Network prediction of $Cu–Al_2O_3$ composite properties prepared by powder metallurgy method

*Mostafa Amirjan**, *Hamid Khorsand*, *Mohammad Hossein Siadati*, *Reza Eslami Farsani*

Material Division, Faculty of Mechanical Engineering, K.N. Toosi University of Technology, Tehran, Iran

ARTICLE INFO

Article history:
Received 5 June 2013
Accepted 30 August 2013
Available online 18 October 2013

Keywords:
$Cu–Al_2O_3$ composite
Artificial Neural Network (ANN)
Hardness
Electrical conductivity
Mechanical alloying
Powder metallurgy

ABSTRACT

Artificial Neural Networks (ANNs) are excellent tools for prediction of complex processes that have many variables and complex interactions. In the present study, the properties of copper based composite prepared from sintering of mechanically alloyed powders, were predicted using Artificial Neural Network (ANN) approach. In order to prepare copper based composites, copper powder with four different amounts of Al_2O_3 reinforcement (1, 1.5, 2, 2.5 wt%) were mechanically alloyed and the consolidated compacts of prepared powders were sintered in five different temperatures of 725–925 °C at seven several sintering times of 15–180 min. Hardness and electrical conductivity measurements were performed to evaluate the properties of these composites. Then, for modeling and prediction of hardness and electrical conductivity, a multi layer perceptron back propagation feed forward neural network was constructed to evaluate and compare the experimental calculated data to predicted values. It was found that, in a given sintering temperature of 875 °C, the electrical conductivity increases as the sintering time increases and the amount of Al_2O_3 reinforcement decreases. Also, increasing of reinforcement amount and sintering time in a given sintering temperature of 875 °C leads to a decrease in hardness. Furthermore, electrical conductivity and hardness of specimens have shown a consistency with predicted results of ANN. These trained values had an average error of 3% and 5% for electrical conductivity and hardness values, respectively.

1. Introduction

Copper–alumina ($Cu–Al_2O_3$) composite materials are extensively used as materials for products which require high strength and electrical properties such as electrode materials for lead wires, relay blades, different contact materials, various switches and electrode materials for spot welding due to high conductivity of copper and high hardness and excellent thermal stability of aluminum [1,2]. Several methods have been used for production of these composites such as sol–gel [3], hydrothermal synthesis [4], internal oxidation and mechanical alloying [5,6]. Internal oxidation is the process of formation of corrosion products (e.g. a metal oxide)

* *Corresponding author.*
E-mail addresses: mamirjan@yahoo.com, mostafa.amirjan@gmail.com (M. Amirjan).
2238-7854 http://dx.doi.org/10.1016/j.jmrt.2013.08.001

within the metal bulk. In other words, the corrosion products are created away from the metal surface, and they are isolated from the surface.

Internal oxidation occurs when some components of the alloy are oxidized in preference to the balance of the bulk. In the case of Cu–Al_2O_3 the internal oxidation technology should tackle both Al oxidation in the copper entirely and prevention of fierce oxidation reaction while Al contacts with oxygen directly.

Mechanical alloying (MA) is a solid-state powder processing technique involving repeated cold welding, fracturing, and re-welding of powder particles in a high-energy ball mill. Originally developed to produce oxide-dispersion strengthened (ODS) alloys and composites, MA has now been shown to be capable of synthesizing a variety of equilibrium and non-equilibrium alloy phases starting from blended elemental or pre-alloyed powders. Several studies have been done for characterization and properties of Cu–Al_2O_3 composites [7–9].

Artificial Neural Networks (ANNs) have been emerged as a new branch of computing, suitable for application in a wide range of fields. Numerous studies have been published on the prediction of several composites' properties [10–15].

ANNs are based on the neural structure of the human brain, which processes information between many neurons and in the past few years there has been a constant increase in interest of neural network modeling in different field of materials science [10–15]. The basic unit in ANNs is the neuron. The neurons are connected to each other with weight factor that determines the strength of the inter connections and thus the contribution of that interconnection to the following neurons. ANNs can be trained to perform a particular function by adjusting the values of these weight factors between the neurons either from the information from outside the network or by the neuron themselves in response to input. This is the key to the ability of ANNs to achieve learning and memory.

The multilayered neural network (MLP) is the most widely applied neural network which has been used in most researches so far [11]. A back propagation algorithm can be used to train these multilayer feed forward networks with differentiable transfer function to approximation, pattern association and pattern classification. The term back propagation refers to the process by which derivatives of network error, with respect to network weight and biases can be computed. The training of ANNs by back propagation involves these stages:

- The feed forward of the input training pattern.
- The calculation and back propagation of the associated error.
- The adjustment of weights.

This process can be used with a number of different optimization strategies. Fig. 1 shows a general view of MLP network. As it is seen in the figure a multilayer perceptron (MLP) is a feed forward Artificial Neural Network model that maps sets of input data onto 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.

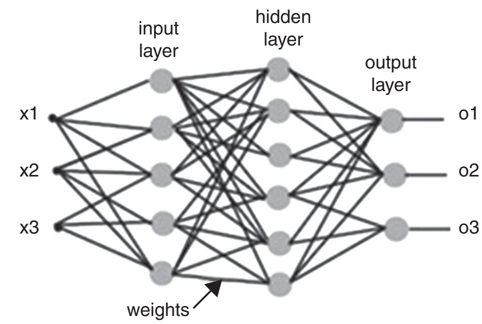

Fig. 1 – General view of a MLP network.

In the present study, a MLP neural network was used for the prediction of experimental results of hardness and electrical conductivity of Cu–Al_2O_3 composites.

2. Materials and methods

High purity copper powder (average size of 45 μm) and Al_2O_3 particles (average size of 5 μm) were used for the production of Cu–Al_2O_3 composites. In order to prepare composite powder with four different amounts of Cu–Al_2O_3 reinforcement (1, 1.5, 2, 2.5 wt%), the powder mixtures were mechanically alloyed in a ball mill in 20 h. and with ball to powder ratio (BPR) of 1:10. Then the composite powders were consolidated to cylindrical shape to achieve green parts. Sintering process was carried out at five different temperatures (725, 775, 825, 875, 925 °C) at seven several sintering times (15, 30, 60, 90, 120, 150, 180 min) in argon atmosphere.

Hardness and electrical conductivity measurements were performed to evaluate the properties of these composites.

A back propagation algorithm was used for modeling and prediction of results with ANNs. In this modeling process the composite composition, time and temperature of sintering were used as input and hardness and electrical conductivity were recorded as output parameters in ANNs design. Then, the neural network was trained using the prepared training set. At the end of the training process the test data were used to check the system's accuracy. MLP architecture and training parameters are presented in Table 1 and ANNs block diagram is given in Fig. 2.

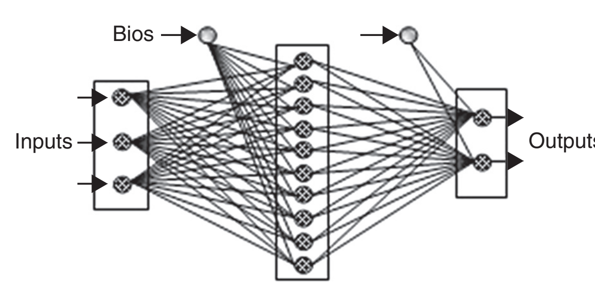

Fig. 2 – ANNs block diagram in this study.

Table 1 – Multilayer perceptron architecture and training parameters.

The number of neurons on the layers	Input: 3, hidden: 10, output: 2
The initial weights and biases	Randomly between −1 and 1
Activation functions for hidden and output layers	Log sigmoid
Training parameters learning rule	Back propagation
Adaptive learning rate of hidden/output layer	0.2
Number of iteration	10000
Momentum constant	0.5
Acceptable mean squared error	0.001

3. Results and discussion

3.1. *The effect of processing parameters on electrical conductivity of Cu–Al_2O_3 composites*

Fig. 3 and Table 2 show the effect of processing parameters consisting sintering temperature and Al_2O_3 reinforcement on the electrical conductivity of composites. As seen, in every group of composites, in a given sintering temperature of 875 °C, electrical conductivity increases as the sintering time increases from 15 to 180 min. Also, in a given sintering time, electrical conductivity decreases as the amount of Al_2O_3 reinforcement increases.

During sintering process, in addition to consolidation and bonding of particles in structure, the recrystallization and growth occurs in microstructure; as the sintering time increases there is enough time for growth of nucleated grains and coarsening. Therefore, coarse grain structure will occur with increased sintering time. As a result, in coarse grain structure of composite there is less volume fraction of grain boundary which acts as a barrier to electrical conductivity; so higher sintering time leads to higher values of electrical conductivity.

Also, Al_2O_3 reinforcement particles disturb the conduction paths of copper (100% IACS). So, the electrical conductivity decreases as the Al_2O_3 reinforcement increases from 1 to 2 wt%; but for 2.5 wt% of Al_2O_3 reinforcement, the decreasing rate will descend. This is because of the decrease of particle distances in the microstructure.

3.2. *The effect of processing parameters on hardness of Cu–Al_2O_3 composites*

As it is seen in Fig. 4, the hardness of composites decreases as the amount of Al_2O_3 reinforcement increases from 1 to 2.5 wt%. Also, in every group of composites, the hardness decreases as the sintering time increases.

Table 2 – Experimental and predicted values of several process conditions.

Samples	Sintering time (min)	Sintering temperature (°C)	Experimental values electrical conductivity (% IACS)	Predicted values electrical conductivity (% IACS)	%Error
Cu–1%Al_2O_3	15	875	55.04469	56.22340541	2.141379
	30	875	57.16256	56.60743055	−0.97114
	60	875	56.68841	55.93407086	−1.33068
	90	875	55.23435	54.07118956	−2.10586
	120	875	56.43553	55.38023394	−1.86991
	150	875	59.47009	58.92729288	−0.91272
	180	875	59.02755	59.28143836	0.430118
Cu–1.5% Al_2O_3	15	875	43.85475	43.91208485	0.130738
	30	875	44.0128	44.74116173	1.654886
	60	875	49.60777	48.61014291	−2.01103
	90	875	46.73126	46.14232366	−1.26026
	120	875	45.78296	46.33401523	1.203625
	150	875	48.31176	47.49071111	−1.69948
	180	875	47.96405	47.86826064	−0.19971
Cu–2% Al_2O_3	15	875	30.35728	31.7252178	4.506128
	30	875	31.11592	33.74424725	8.446889
	60	875	36.93216	34.7990524	−5.77575
	90	875	37.59597	34.17020559	−9.11205
	120	875	33.42345	35.19467747	5.299356
	150	875	37.94368	36.43229274	−3.98324
	180	875	36.90055	37.09723153	0.533004
Cu–2.5% Al_2O_3	15	875	34.56141	34.11000687	−1.30609
	30	875	35.13039	34.61242822	−1.4744
	60	875	35.82581	34.30324133	−4.24992
	90	875	33.13896	32.99999485	−0.41934
	120	875	32.25388	33.88568619	5.059255
	150	875	35.66776	35.34975455	−0.89158
	180	875	36.33157	36.3007237	−0.0849

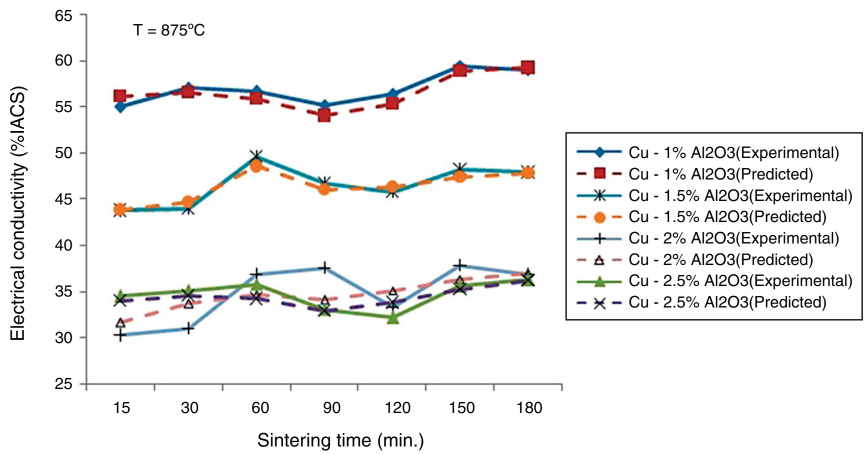

Fig. 3 – Experimental and predicted results of the effect of chemical composition and sintering time on the electrical conductivity of Cu–Al_2O_3 composites.

With respect to strengthening mechanism of Orawan, with increasing reinforcement amount, the distances between particles in the microstructure will decrease. Therefore, the dislocations can encompass the particles easily and lead to lower values of hardness. Also, the grain size of the composite matrixes microstructure increases with increasing sintering time. According to Hall–Petch effect, larger grain size in microstructure leads to a decrease in hardness values.

3.3. ANN approach to electrical conductivity and hardness predictions

In this study, prediction of electrical conductivity and hardness of Cu–Al_2O_3 MMC were performed using a back propagation neural network. These experimental results have been compared with ANNs results. Iteration number has been selected 10,000. Three input neurons, 10 neurons in intermediate layers and 2 output neurons [3:10:2] have been selected for this study. The learning rate and momentum values have been selected as 0.2 and 0.5, respectively.

- Sintering temperature, time and reinforcement values were used as input while the electrical conductivity and hardness were the outputs of the model. These data were obtained from experimental work.
- Figs. 3 and 4 show the predicted values of electrical conductivity and hardness in comparison with experimental data, respectively. Electrical conductivity and hardness of specimens have shown a consistency with predicted results. Theses trained values had an average error of 3% in electrical conductivity and 5% in hardness values.

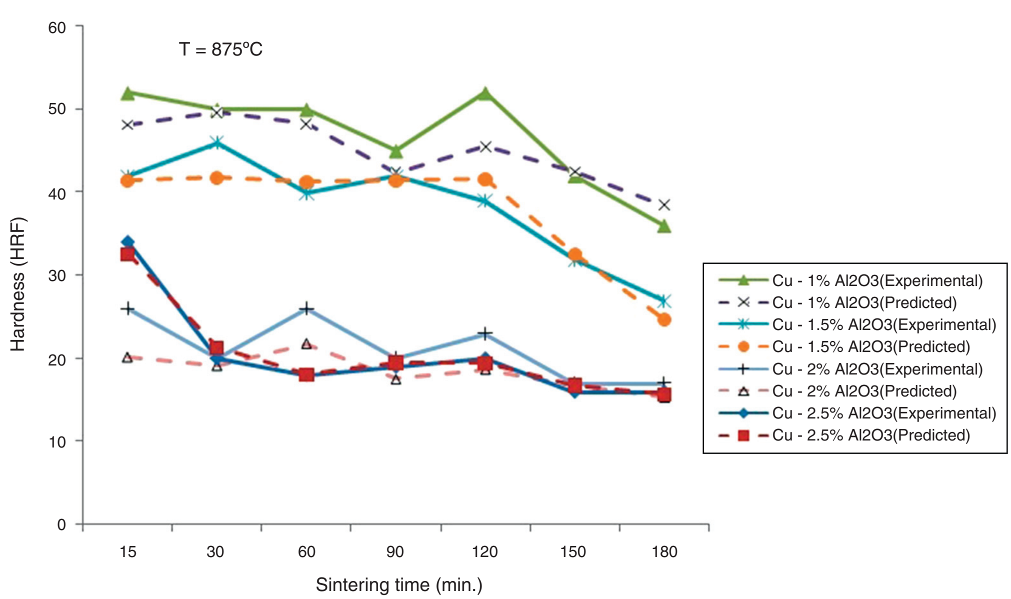

Fig. 4 – Experimental and predicted results of the effect of chemical composition and sintering time on the hardness of Cu–Al_2O_3 composites.

4. Conclusions

In the present study, prediction of $Cu–Al_2O_3$ composites under several processing conditions was performed. The following results were obtained:

- Artificial Neural Network (ANN) can be used as an efficient tool in predicting composite properties. Under given conditions and prescribed materials predicted values of properties can be utilized by designers and process engineers and account as a cost saving item in the process.
- Experimental electrical conductivity and hardness of specimens have shown a consistency and good agreement with predicted results of ANNs model.
- In this study, designed ANN model predicted the electrical conductivity with an average error of 3% and hardness with about 5%.

Conflicts of Interest

The authors declare no conflicts of interest.

REFERENCES

[1] Korać M, Kamberović Ž, Andjić Z, Filipović M, Tasić M. Sintered materials based on copper and alumina powders synthesized by a novel method. Science of Sintering 2010;42:81–90.

[2] Rajković V, Božić D, Popović M, Jovanović M. Properties of $Cu–Al_2O_3$ powder and compact composites of various starting particles size obtained by high energy milling. Association of Metallurgical Engineers of Serbia AMES; Metalurgia-Journal of Metallurgy (MJOM) 2009;15(1):45–52.

[3] Ruys AJ, Mai Y-W. The nanoparticle-coating process: a potential sol–gel route to homogeneous nanocomposites. Materials Science and Engineering A 1999;265:202–7.

[4] Anđić Z, Korać M, Kamberović Ž, Vujović A, Tasić M. Analysis of the properties of a $Cu–Al_2O_3$ sintered system based on ultra fine and nanocomposite powders. Science of Sintering 2007;39:145152.

[5] Jena P, Brocchi E, Motta M. Characterization of $Cu–Al_2O_3$ nano-scale composites synthesized by in situ reduction. Materials Science and Engineering 2001;C15: 175177.

[6] Rajković V, Božić D, Stašić J, Dimčić B. Properties of $Cu–Al_2O_3$ composites obtained by high energy milling and internal oxidation. Association of Metallurgical Engineers of Serbia 2009;15:181–8.

[7] Rajkovic V, Bozic D, Jovanovic MT. Characteristics of $Cu–Al_2O_3$ composites of various starting particle size obtained by high-energy milling. Journal of the Serbian Chemical Society 2009;74(5):595–605.

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

[9] Mukhtar A, Zhang DL, Kong C, Munroe P. Variation in hardness of ultrafine grained $Cu–Al_2O_3$ composite hollow balls and granules produced by high energy mechanical milling. Materials Forum 2008;32:105–9.

[10] Mathur S, Gope PC, Sharma JK. Prediction of fatigue lives of composites material by artificial neural network. In: Proceedings of the SEM 2007 annual conference and exposition. 2007.

[11] Neural networks which identify composite factors. In: European symposium on artificial neural networks. 1999.

[12] Koker R, Altinkok N. Modelling of the prediction of tensile and density properties in particle reinforced metal matrix composites by using neural networks. Materials and Design 2005:1–7.

[13] Durmus H, Ozkaya E, Meric C. The use of neural networks for the prediction of wear loss and surface roughness of AA6351 aluminum alloy. Materials and Design 2006;27:156–9.

[14] Perzyk M, Kochanski AW. Prediction of ductile cast iron quality by artificial neural networks. Journal of Materials Processing Technology 2001;109:305–7.

[15] Taskin M, Çaligulu U, Dikbas H. Artificial Neural Network (ANN) approach to prediction of diffusion bonding behaviour (shear strength) of SiCp reinforced aluminium metal matrix composites. Journal of Yasar University 2008;3(12):1811–25.