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Investigation of Manufacturing Parameters on the Mechanical Properties of Powder Metallurgy Magnesium Matrix Nanocomposite by Artificial Neural Networks

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In present study, Artificial Neural Network (ANN) approach to prediction of the ODS Magnesium matrix composite mechanical properties obtained was used. Several composition of Mg- Al_2O_3 composites with four different amount of Al_2O_3 reinforcement with four different size of nanometer to micrometer were produced in different sintering times. The specimens were characterized using metallographic observation, microhardness and strength (UTS) measurements. Then, for modeling and prediction of mentioned conditions, a multi layer perceptron back propagation feed forward neural network was constructed to evaluate and compare the experimental calculated data to predicted values. In neural network training modules, different composition, sintering time and reinforcement size were used as input (3 inputs), hardness and Ultimate Tensile Strength(UTS) were used as output. Then, the neural network was trained using the prepared training set. At the end of training process the test data were used to check the system's accuracy. As a result, the comparison of neural network output results with the results from experiments and empirical relationship has shown good agreement with average error of 2.5%.

Keywords: Mg-Al_2O_3 Nanocomposite, Artificial neural network, Hardness, UTS, Powder metallurgy.

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1. INTRODUCTION

Metal Matrix Composites (MMCs) have been widely recognized to have relatively superior mechanical properties, such as better wear resistance, higher elastic modulus and yield strength, as compared to the unreinforced monolithic metal. As compared to fiber reinforced MMCs, particulate reinforced MMCs are gaining popularity due to their ease of fabrication, high throughput and lower manufacturing cost [1]. Among the various types of MMCs, light-weight MMCs such as magnesium (Mg) based composites are arousing more interest due to their potential applications in aerospace, automotive and sports equipment industries. With a judicious selection of particulate reinforcements, magnesium based composites are known to have high specific mechanical properties [2], low density, improved thermal and dimensional stability and better damping properties.

Al2O3 short fibers and particulates are commonly used as reinforcement for magnesium and have been shown to improve the tensile strength of magnesium alloys [3,4] and thermal stability of the grain structure in pure magnesium [5]. Additionally, recent studies on reinforcing pure magnesium with sub-micron and nano-size Al_2O_3 particulates have shown promising results with simultaneous increment observed in both strength and ductility of magnesium using both solidification and powder metallurgy techniques [6,7].

Artificial Neural Networks (ANNs) have been emerged as a new branch of computing, suitable for application in a wide range of fields. A lot of studies have been published in which the prediction of several composites properties [8-10].

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 [9-12]. 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 ability of ANNs to achieve learning and memory.

The multilayered neural Network (MLP) is the most widely applied to neural network which has been used in most researches so far[7]. 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 stage:

– 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. In present study, a MLP neural network was used to prediction and confirmation of experimental results of microhardness and UTS of Mg-Al_2O_3 composites.

2. EXPRIMENTAL PROCEDURE

Magnesium powder (average size of 50 μm) and Al_2O_3 particles with four different size of 50 nm, 200 nm, 1 μm and 50 μm were used for production of Mg-Al_2O_3 nanocomposites. Also, several weight percent

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of Al_2O_3 reinforcement (0.25, 0.5, 1 and 1.5%) were used. The powder mixture were mechanically alloyed in a ball mill in 15 hr and with ball to powder ratio (BPR) of 1:10. Then the composite powders were consolidated to green parts. Sintering process was carried out at 610 °C at several sintering time (15, 30, 60, 90, 120, 150 min.) in reducing atmosphere.

Hardness and Ultimate Tensile strength(UTS) measurements were performed to evaluating 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, sintering time and reinforcement size were used as input and hardness and UTS were recorded as output parameters in ANNs design. MLP architecture and training parameters were presented in Table 1 and ANNs block diagram given at Fig. 1.

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 to 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	15000
Momentum constant	0.5
Acceptable mean squared error	0.001

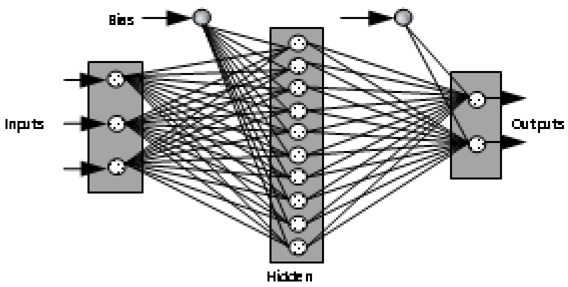

Fig. 1 – ANNs Block diagram in this study

3. RESULTS AND DISCUSSIONS

3.1 The Effect of Sintering Time on the Mechanical Properties

Fig. 2, Fig. 3 and Table 2, Table 3 are shown the effect of processing parameters consisting sintering time and Al_2O_3 reinforcement(amount and size) on the microhardness and UTS of composites. As seen, in every group of composites, in a given sintering temperature of 61 °C, hardness and UTS increases as the sintering time increases from 15 to 90 min and then show a decrease in hardness from 90 to 15 min. 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 be occur with increased sintering time.

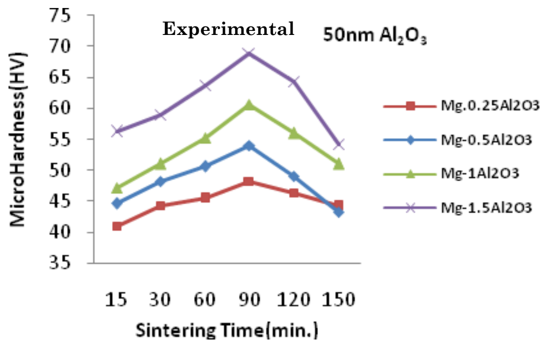

Fig. 2 – The effect of sintering time on the microhardness of Mg-Al_2O_3 composite with nano size reinforcement

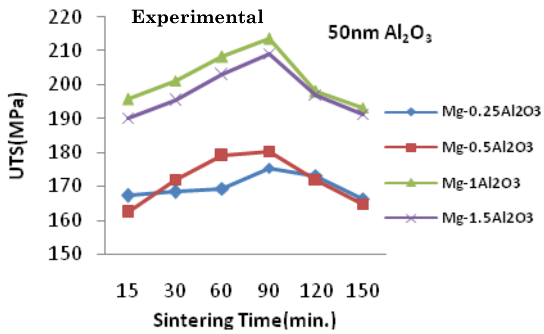

Fig. 3 – The effect of sintering time on the UTS of Mg-Al_2O_3 composite with nano size reinforcement

3.2 The effect of amount and Reinforcement size on the Mechanical properties

As it is see in Fig. 4 and Fig. 5, in a given sintering time, hardness and UTS increase as the amount of reinforcement from 0.25 to 1.5% wt. Also, hardness and UTS of composites decrease as the size of reinforcement increase from nanosize to micron level. Higher values of microhardness and UTS observed for the composite with 1.5wt % of 50 nm reinforcement at sintering time of 90 min.

The increase in hardness of the magnesium matrix with the addition of nano-size reinforcements can be attributed primarily to the: (i) presence of harder nanopowder reinforcement in the matrix and (ii) higher constraint to the localized matrix deformation due to the presence of harder phases. These results are consistent with the trend observed by other investigators [13-15]. The increase in UTS can be attributed to the combined influence of: (i) work hardening due to the strain misfit between the reinforcing particulates and the matrix, (ii) the formation of internal thermal stresses due to different thermal expansion behavior between Al_2O_3 reinforcement and the matrix, (iii) Orowan strengthening and (iv) reduction in grain size. Orowan strengthening due to the presence of sub-micron and nano-size particulates has been shown to contribute to the improvement in the yield strength of particulate reinforced metal matrix composites [14-17].

Table 2 – The effect of processing parameters on the microhardness and UTS values of composites(Experimental and Predicted Values)

Comp.	Sintering Time(Min.)	Reinforcement size(μm)	Microhardness(HV)			UTS(MPa)		
			Experimental Values	Predicted Values	%Error	Experimental Values	Predicted Values	%Error
Mg-0.25Al_2O_3	90	0.05	48.234	47.893	-0.712	175.450	177.034	0.894743
		0.20	43.623	43.004	-1.4394	168.679	168.123	-0.33071
		1.00	40.033	38.984	-2.69085	159.467	158.943	-0.32968
		50.00	36.970	36.000	-2.69444	151.349	152.496	0.752151
Mg-0.50Al_2O_3	90	0.05	54.023	55.012	1.79779	180.289	181.338	0.578478
		0.20	49.738	48.234	-3.11813	173.945	174.034	0.051139
		1.00	42.546	43.258	1.645938	165.345	165.007	-0.20484
		50.00	39.134	38.945	-0.4853	160.223	159.582	-0.40167
Mg-1.00Al_2O_3	90	0.05	60.695	61.485	1.284866	213.556	212.421	-0.53432
		0.20	52.078	53.674	2.973507	203.669	202.497	-0.57877
		1.00	47.893	46.896	-2.12598	195.234	196.329	0.557737
		50.00	42.356	41.557	-1.92266	189.492	191.056	0.818608
Mg-1.50Al_2O_3	90	0.05	68.945	69.456	0.735718	209.168	208.228	-0.45143
		0.20	62.567	61.789	-1.25912	200.005	201.834	0.90619
		1.00	56.355	55.006	-2.45246	191.407	190.491	-0.48086
		50.00	51.667	53.045	2.597794	185.038	186.330	0.693393

Mathematically, the contribution to yield strength by Orowan strengthening can be expressed as [18]:

$$\sigma_{orowan} = M\frac{0.4G.B}{\pi\bar{\lambda}}\ln\left(\frac{\bar{d}}{d}\right)/\sqrt{1-\nu_{Mg}}$$

where $\bar{d} = \sqrt{2/3d}$, ν_{Mg} is the Poisson's ratio for Mg and $\bar{\lambda}$ is the mean inter-particle distance given by $\bar{\lambda} = \bar{d}\ \sqrt{\pi/4f} - 1$.

The increase in strength of the Mg/Al_2O_3 composites can be partly attributable to the reduction in grain size. The refinement in grain size arises due to the presence of reinforcing particles which acts as nucleation sites during recrystallization and the pinning of grain boundaries by the particles resulting in limited grain growth.

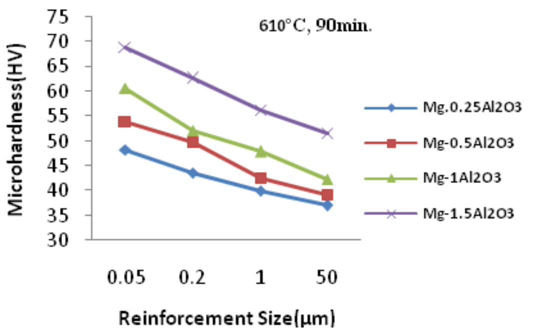

Fig. 4 – The effect of Reinforcement size on the microhardness of composites at sintering time of 90min

In this study, prediction of Microhardness and UTS of Mg-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 15000. 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.

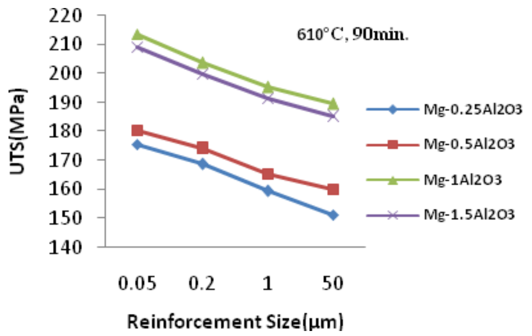

Fig. 5 – The effect of Reinforcement size on the UTS of composites at sintering time of 90 min

4. CONCLUSIONS

In present study, prediction of Mg-Al_2O_3 composites under several processing conditions was performed. Following results were obtained:

– Sintering time and reinforcement size and amount were used as input while the microhardness and UTS were the output of the model. These data were obtained from experimental work.

– Fig. 6 and Fig. 7 shows the predicted values of microhardness and UTS, respectively. Microhardness and UTS of specimens have shown a consistency with predicted results. Theses trained values had an average error of 2.5% in Microhardness and 1.5% in UTS values.

– Artificial Neural Network (ANNS) can be used as efficient tool in predicting composite properties. Under given condition and prescribed materials predicted values of properties can be utilized by designers and process engineers and account as a cost saving item in process.

– Experimental microhardness and UTS of specimens have shown a consistency and good agreement with predicted results of ANNs model.

– In this study, designed ANN model was predicted the microhardness with an average error of 2.5% and UTS with about 1.5%.

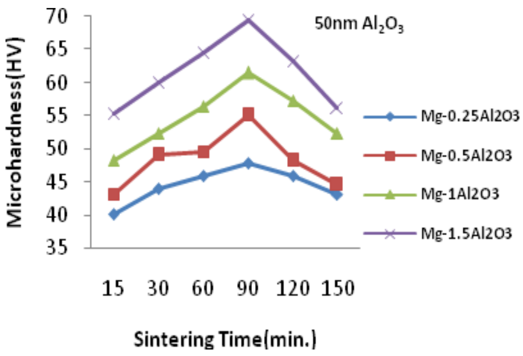

Fig. 6 – The Effect of sintering time on the microhardness of Mg-Al_2O_3 composite with nano size reinforcement (Predicted)

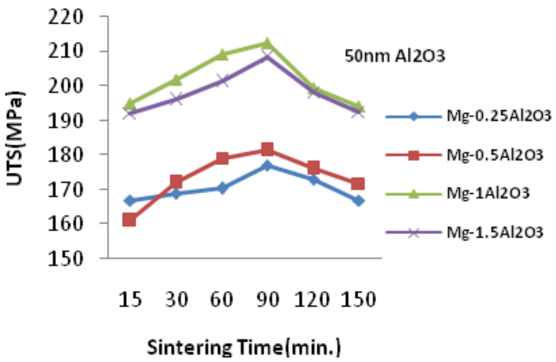

Fig. 7 – The Effect of sintering time on the UTS of Mg-Al_2O_3 composite with nano size reinforcement(Predicted)

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