Modeling of the Prediction of Densification Behavior of Powder Metallurgy Al–Cu–Mg/B₄C Composites Using Artificial Neural Networks

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Abstract Al–Cu–Mg/B₄Cp metal matrix composites with reinforcement of up to 20 wt% were produced using the powder metallurgy technique. The effects of reinforcement ratio, reinforcement size, milling time, and compact pressure on the density and porosity of the composites reinforced with 0, 5, 10, and 20 wt% B₄C particles were studied. Moreover, an artificial neural network model has been developed for the prediction of the effects of the manufacturing parameters on the density and porosity of powder metallurgy Al–Cu–Mg/B₄Cp composites. This model can be used for predicting the densification behavior of Al–Cu–Mg/B₄Cp composites produced under reinforcement of different sizes and amounts with various milling times and compact pressures. The mean absolute percentage error for the predicted values did not exceed 1.6%.

KEY WORDS: Al alloys; Composite; Mechanical milling; Metal matrix composite; Artificial neural network

1 Introduction

Particle-reinforced metal matrix composite materials (PMMCs) have received considerable attention due to their high strength, high stiffness, superior wear resistance, and retention of strength at elevated temperatures [1, 2]. They have been widely used in the fields of aeronautical, space, automotive, mechanical, and electronics. A better understanding of the mechanical behavior of the particle-reinforced metal matrix composites will improve material design and processing [3, 4]. There were several

fabrication techniques available in manufacturing the MMC materials, including powder metallurgy [5, 6], stir casting [7], thixomolding [8], liquid metal infiltration [9], and squeeze casting [10].

The powder metallurgy is in many cases the only suitable method to obtain the metal matrix composites. Compared with melting method, the most important advantage of powder metallurgy method is the low processing temperature. That is why undesired phases between the matrix phase and the reinforcement phase are eliminated. Moreover, reinforcement particles are also well-distributed in the matrix. Another significant feature is the ability to produce near net-shape parts, which is cost effective [11]. Wang et al. [12] studied that the production of MgCNi₃ intermetallic compound with the Mg, Ni, and graphite powders by mechanical alloying technique. They stated that the formation of MgCNi₃ can be attributed to the specific microstructure caused by the MA process. The high-density lattice defects (dislocations, vacancies) and interfacial area are formed during the milling process. Additionally, the refined powders were mixed thoroughly during the milling process, which enhances the atomic

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diffusion and rearrangement. Both the above factors surmount the kinetic barrier of the alloying reaction and make it possible that the reaction occurs at ambient temperature. Zakeri *et al.* [13] investigated that the mean grain size of nanomaterials fabricated by mechanical alloying has been modeled by artificial neural networks (ANNs). They reported that experimental variables such as the mean grain size, milling time, vial speed and ball-to-powder ratio, and structural variables such as annealing temperature and produced phases after mechanical alloying could be employed as inputs for predicting the mean grain size values of synthesized nanocomposite powders. Akarpour *et al.* [14] investigated the microstructure and compressibility of SiC nanoparticles reinforced Cu nanocomposite powders processed by mechanical alloying method. They observed that the compressibility of the composite powder decreased with increasing milling time and SiC content due to the changes in morphology and hardness of the powders.

Recently, there has been increased interest in ANN modeling within different fields of materials science [15, 16]. ANN is a well established field over the last 20 years because it can often solve problems much faster compared with other approaches with the additional ability to learn from a small set of experimental data [1, 2]. The use of ANNs represents a new methodology in many different applications of the composite materials including prediction of physical and mechanical properties [17–19]. However, an artificial neural network (ANN) model has not yet been established for understanding the effects of reinforcement size, reinforcement ratio, compact pressure, and milling time on the density and porosity of Al2024–B₄C MMCs produced by powder metallurgy. The aim of this study is to predict the effects of reinforcement size, reinforcement ratio, compact pressure, and milling time on the density and porosity of Al–Cu–Mg alloy/B₄C MMCs produced by powder metallurgy with the use of ANN.

2 Experimental

2.1 Materials and Method

The weight percentages of the B₄C particle in the composites are 5, 10, and 20%, respectively. Al–Cu–Mg alloy powders with an average particle size of about 75 μm and B₄C powders with particle sizes of 49 and 5 μm were used as initial materials. The mixtures were milled using a planetary ball mill method (Fritsch “Pulverisette 7, Premium line”) for different milling time of 0.5, 1, 2, 5, 7, and 10 h. A ball-to-powder weight ratio of 10:1 was kept constant in the tungsten carbide vials. Methanol (2 wt%) was used as a process control agent. The rotational speed was controlled at 400 r/min. The above mixtures milled for

0.5, 1, 2, 5, 7, and 10 h were loaded into a steel die and hot pressed at 400 °C under 200, 400, and 600 MPa. Graphite was coated on the inner wall of the mold and surface of the samples as lubricant. The schematic design of densification die is shown in Fig. 1. The specimens were prepared by grinding paper from 400 to 1,200 grit and were polished by 0.1 μm alumina, and subsequently ultrasonically cleaned and etched using a reagent comprising 2.5 mL HNO₃, 1.5 mL HCl, 1 mL HF, and 95 mL distilled water (Keller’s solution). The microstructure of the composites was characterized by means of scanning electron microscopy (SEM). The density (ρ) of compacts was determined by the Archimedes method. The theoretical density of compacts was calculated from the simple rule of mixtures taking the fully dense values for Al–Cu–Mg alloy (2.8 g/cm³) and B₄C (2.52 g/cm³). For each sample, ten density tests were applied in order to eliminate the possible errors. This approach increased the accuracy of the training and testing data as well as accuracy of prediction models.

3 Artificial Neural Network (ANN) Model

Usually neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The training of ANN is based on a comparison of the output and

Fig. 1 Schematic diagram of the compaction die

the target, until the network output matches the target. Typically many such input/target pairs are used to train a network. That means that for reliable training and performance of any neural networks we need an appropriate database. Using such a database, we can train ANN to perform complex functions. Commonly, a neural network modeling follows these steps: database collection; analysis and pre-processing of the data; training of the neural network: this includes choice of architecture, training functions, training algorithms, and parameters of the network; test of the trained network; using the trained ANN for simulation and prediction [19, 20].

The basic neural cell model is shown in Fig. 2. In the artificial neuron, the main components include weights, addition function, activation function, and outputs. Inputs (x_i) are data, obtained from the external environment or the other artificial neurons. The quantities (w_{ij}) demonstrate the effect of a data point on an arrival of an artificial neural cell. The addition function (threshold function, Eq. (1)) (net_j) calculates the net input on a neural cell. The sigmoid function (Eq. (2)) is the most common activation function in the ANN because it combines nearly linear behavior, curvilinear behavior, and nearly constant behavior. All of these components depend on the value of the input [21, 22]. In the cell model, a bias with +1 value may increase the net input or polarization threshold input (θ_j) by a value of -1, thereby decreasing the net input according to

$$\text{net}_j = \sum_{i=1}^n x_i w_{ij} - \theta_j, \quad (1)$$

where x_i indicates the i . input, w_{ij} is the connection weight from j . element to i . element, θ_j is the polarization value (negative of the threshold value), and n indicates the sent input signal of the artificial neuron number in the previous layer.

The artificial neuron output value, which depends on the selected activation function employs a sigmoid function as the activation function [18, 19, 23] and is calculated using

Eq. (2). The produced output is sent via the network connection between different cells, as explained by

$$y_j = f(\text{net}_j) = \frac{1}{1 + e^{-\text{net}_j}}. \quad (2)$$

When more than one parallel processing artificial neuron is necessary, a multi-layered network structure is used. Figure 3 shows a typical ANN architecture consisting of three layers one input layer, one hidden layer, and an output neuron.

In the structure of a multi-layered ANN, there are mainly three layers, consisting of an input layer with artificial neural cells that are connected to each other in different ways, an output layer, and two hidden layer (intermediate layer). The input layer is the first layer and is responsible for receiving the incoming data for the ANN and for delivering the data to intermediate layer. The hidden layer processes the information that comes from the input layer and sends it to the output layer. The neurons in the hidden layer do not have any connection to the external environment. The output layer processes the information coming from the intermediate layer and produces output data for the input layer of the network, which sends this to the outside world.

3.1 Collecting the Experimental Data

In this study, the alterations of the green density, the sintered density, and the hardness of composites produced by mechanical milling method were modeled by the ANN. To examine the effects of the reinforcement size, reinforcement ratio, compact pressure, and milling time on the density and porosity, the experimental data were grouped into training and test data. The training data were used in the forecast model, as shown in Table 1.

In the research for the practical application of materials, it is necessary to prepare a database of the experimental results which is large enough to develop an ANN with good performance. The architecture, transfer function,

Fig. 2 Artificial neural cell (artificial neuron)

Fig. 3 A typical multi-layered ANN architecture

training algorithm, and other parameters of the neural network should be carefully set and modified during optimization. Thus, the well-trained neural network can be used to obtain the solutions of new input data in the same domain of the experimental database. This process can be summarized in the following four stages: (1) collect and pre-process the experimental data; (2) train the ANN and optimize its configuration; (3) evaluate the performance of the ANN returning to stage 2 if the performance is not satisfactory; (4) use the trained ANN for simulation or prediction [24].

Different models have different network structures, and thus different learning parameters were examined in the training period. To test the performance of the networks, the models were tested with the data that were not used in the training set. This method made it possible to obtain the most precise results. The estimated values from the tests were then compared to the measured values. When designing ANNs and selecting definite design parameters, the selection can be more or less subjective, but is very important to achieve the optimal neural network performance. The information that determines network performance is obtained by the aid of diverse identification methods that attempt to minimize the difference between the output calculated by the ANN and the desired output. From the well known and widespread identification tools, the root-mean squared error (RMSE) and the mean absolute percentage error (MAPE) values are calculated from Eqs. (3) and (4) [25]. Models that produce the best-estimated values were selected as the forecasting models.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i - td_i)^2}, \quad (3)$$

$$\text{MAPE} = \frac{1}{N} \left(\sum_{i=1}^N \left[\left| \frac{t_i - td_i}{t_i} \right| \right] \right) \times 100, \quad (4)$$

where t_i is the real value, td_i is the model prediction value, and N is the number of testing data.

Table 3 shows the actual values, degrees of deviation, and percentage error rates; the RMSE and MAPE were calculated using the estimated models.

3.2 Neural Network Architecture

Figure 4 shows the ANN models containing one input layer, two hidden layers, and one output layer. The selected ANN model represents the prediction model that produced the closest values to the measured values for density and porosity. The milling time, reinforcement ratio, reinforcement size, and compact pressure were used as input variables, while the density and porosity values were used as output variables in the ANN models. The processing element numbers (neurons) of the hidden layers were 3 and 6 for the model in Fig. 4.

3.3 Network Training and Testing

A forward and backward feed propagation multi-layered ANN was used for solving problems, and the network training and testing was carried out using the MATLAB software package. In this study, the hyperbolic tangent sigmoid function (tansig) (Eq. (2)) and the linear transfer function (purelin) were used as the activation transfer functions; the resilient back propagation function (trainrp) was used as the training algorithm; the gradient descent with a momentum back propagation algorithm (traingdm) was used as the learning rule; and the mean square error (MSE) was used as the performance function. To ensure an equal contribution of each parameter in the model, the training and test datasets were normalized (−1, 1 range) due to the use of the hyperbolic tangent sigmoid function in the model and network, which allowed the data to be

Table 1 Experimental data and predicted output from the ANN network for training set

Sample ID	Compact pressure (MPa)	Reinforcement ratio (wt%)	Reinforcement size (μm)	Milling time (h)	Density (g/cm^3)			Porosity (%)		
					Measured	Predicted	Error (%)	Measured	Predicted	Error (%)
1	200	0	0	0	2.675	2.673	0.07	4.46	4.275	4.14
3	200	0	0	1	2.645	2.641	0.16	5.54	5.392	2.67
5	200	0	0	5	2.621	2.619	0.08	6.39	6.125	4.15
7	200	0	0	10	2.603	2.599	0.17	7.04	6.827	3.02
9	200	5	49	0.5	2.645	2.647	−0.06	5.1	5.206	−2.07
10	200	5	49	1	2.63	2.637	−0.28	5.6	5.529	1.27
14	200	5	49	10	2.566	2.563	0.12	7.9	8.078	−2.25
17	200	10	49	1	2.587	2.580	0.26	6.67	6.792	−1.83
19	200	10	49	5	2.54	2.533	0.29	8.37	8.610	−2.87
22	200	20	49	0	2.583	2.581	0.09	5.87	6.048	−3.03
23	200	20	49	0.5	2.551	2.554	−0.12	7.04	6.976	0.91
25	200	20	49	2	2.53	2.534	−0.14	7.8	7.709	1.17
27	200	20	49	7	2.42	2.415	0.21	11.81	11.930	−1.01
28	200	20	49	10	2.415	2.403	0.49	12	12.348	−2.90
31	200	5	5	1	2.624	2.626	−0.08	5.81	5.905	−1.64
33	200	5	5	5	2.585	2.593	−0.30	7.21	7.036	2.41
35	200	5	5	10	2.554	2.556	−0.07	8.33	8.325	0.06
36	200	10	5	0	2.598	2.598	−0.01	6.28	6.084	3.12
39	200	10	5	2	2.56	2.557	0.11	7.65	7.571	1.03
41	200	10	5	7	2.455	2.454	0.05	11.44	11.401	0.34
43	200	20	5	0	2.565	2.566	−0.05	6.53	6.548	−0.28
44	200	20	5	0.5	2.539	2.539	0.00	7.47	7.489	−0.26
45	200	20	5	1	2.532	2.531	0.06	7.73	7.784	−0.70
49	200	20	5	10	2.385	2.399	−0.57	13.08	12.511	4.35
50	400	0	0	0	2.725	2.723	0.08	2.68	2.535	5.39
51	400	0	0	0.5	2.709	2.703	0.23	3.25	3.238	0.36
53	400	0	0	2	2.687	2.685	0.09	4.04	3.877	4.03
54	400	0	0	5	2.67	2.660	0.37	4.64	4.680	−0.86
57	400	5	49	0	2.71	2.716	−0.22	2.73	2.772	−1.55
58	400	5	49	0.5	2.693	2.696	−0.13	3.34	3.458	−3.52
60	400	5	49	2	2.673	2.674	−0.04	4.06	4.244	−4.52
62	400	5	49	7	2.623	2.620	0.12	5.85	6.081	−3.94
64	400	10	49	0	2.663	2.667	−0.16	3.93	3.704	5.75
65	400	10	49	0.5	2.641	2.647	−0.21	4.73	4.457	5.77
69	400	10	49	7	2.517	2.526	−0.34	9.2	9.014	2.02
71	400	20	49	0	2.625	2.629	−0.14	4.34	4.317	0.52
72	400	20	49	0.5	2.6	2.605	−0.19	5.25	5.155	1.80
75	400	20	49	5	2.563	2.552	0.43	6.6	7.083	−7.32
77	400	20	49	10	2.46	2.449	0.45	10.35	10.705	−3.43
79	400	5	5	0.5	2.682	2.686	−0.16	3.73	3.817	−2.34
80	400	5	5	1	2.675	2.673	0.06	3.98	4.264	−7.13
83	400	5	5	7	2.61	2.611	−0.05	6.32	6.385	−1.02
85	400	10	5	0	2.658	2.652	0.23	4.11	4.240	−3.17
87	400	10	5	1	2.625	2.619	0.23	5.3	5.451	−2.86
89	400	10	5	5	2.59	2.583	0.29	6.57	6.902	−5.05
91	400	10	5	10	2.491	2.501	−0.42	10.14	9.932	2.05

Table 1 continued

Sample ID	Compact pressure (MPa)	Reinforcement ratio (wt%)	Reinforcement size (μm)	Milling time (h)	Density (g/cm^3)			Porosity (%)		
					Measured	Predicted	Error (%)	Measured	Predicted	Error (%)
92	400	20	5	0	2.62	2.618	0.08	4.52	4.705	−4.10
95	400	20	5	2	2.561	2.562	−0.03	6.67	6.676	−0.10
96	400	20	5	5	2.524	2.541	−0.67	8.02	7.480	6.73
99	600	0	0	0	2.766	2.760	0.22	1.21	1.233	−1.92
101	600	0	0	1	2.741	2.734	0.27	2.11	2.152	−1.98
102	600	0	0	2	2.728	2.722	0.22	2.57	2.565	0.19
105	600	0	0	10	2.688	2.682	0.21	4	3.893	2.67
107	600	5	49	0.5	2.735	2.741	−0.22	1.83	1.898	−3.73
110	600	5	49	5	2.685	2.692	−0.25	3.63	3.571	1.63
112	600	5	49	10	2.659	2.663	−0.15	4.56	4.571	−0.25
115	600	10	49	1	2.7	2.698	0.06	2.6	2.595	0.18
117	600	10	49	5	2.665	2.665	0.01	3.86	3.945	−2.19
118	600	10	49	7	2.622	2.619	0.12	5.41	5.629	−4.06
120	600	20	49	0	2.687	2.685	0.09	2.08	2.136	−2.68
123	600	20	49	2	2.625	2.632	−0.26	4.34	4.075	6.10
125	600	20	49	7	2.525	2.536	−0.42	7.98	7.599	4.78
126	600	20	49	10	2.512	2.508	0.15	8.45	8.569	−1.41
129	600	5	5	1	2.711	2.720	−0.32	2.69	2.648	1.55
131	600	5	5	5	2.679	2.685	−0.24	3.84	3.790	1.31
133	600	5	5	10	2.652	2.656	−0.16	4.81	4.808	0.04
134	600	10	5	0	2.713	2.716	−0.11	2.13	1.886	11.48
137	600	10	5	2	2.68	2.679	0.03	3.32	3.274	1.40
139	600	10	5	7	2.611	2.606	0.19	5.81	6.038	−3.93
141	600	20	5	0	2.678	2.672	0.24	2.41	2.652	−10.03
143	600	20	5	1	2.641	2.636	0.20	3.75	3.939	−5.05
144	600	20	5	2	2.617	2.621	−0.16	4.63	4.513	2.54
147	600	20	5	10	2.5	2.500	−0.01	8.89	8.854	0.40
MAPE					0.093			1.400		
RMSE					0.004			0.136

Fig. 4 ANN architecture selected as a prediction model for density and porosity

translated into the original value, with a reverse normalizing process for the interpretation of the results. The normalization (scaling) operations were carried out using Eq. (5)

$$X_{\text{norm}} = 2 \times \frac{X - X_{\min}}{X_{\max} - X_{\min}} - 1, \quad (5)$$

where X_{norm} is the normalized value, X is the true value of the variable, $X_{\min}$ is the minimum value of the data set, and $X_{\max}$ is the maximum value of the data set.

It was decided that the 0.001 targeted error values would be sufficient for the training of the ANN. Figure 5 shows the iteration dependent error variation quantity for an ANN selected for the density and porosity values.

It is important to evaluate the performance of the ANN model. This is done by separating the data into two sets the training set and the validating set. The parameters (i.e., the value of the synaptic weights) of the network are computed 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 [1]. The validation data were used in the forecast model, as shown in Table 2.

4 Results and Discussion

4.1 Microstructure Evolution of the Composite

The performances of the particle-reinforced metal matrix composites in industrial applications are strongly dependent on their physical and microstructural features. However, microstructure analysis is one of the most difficult problems in powder metallurgy due to the absence of homogeneous distribution of the reinforcement particles in the matrix alloy. The main objective of the mechanical alloying was to ensure that a homogeneous distribution of B_4C reinforcement particles in an aluminum matrix was achieved after milling. The reason behind this is the fact that a uniform distribution of the reinforcements could

potentially result in the composites with improved properties. However, achieved uniform distribution requires careful synthesis since the agglomeration of the reinforcement particles would be a major limitation. Figure 6 shows the microstructure and distribution of the B_4C particle milled from 0 to 10 h. The reinforcement particles adhere together and a heterogeneous distribution of B_4C particles is obtained as seen in Fig. 6a. The particle distribution was not uniform and the distance between alumina particles was high (1 h, Fig. 6b), and the increase in milling time caused the big and brittle B_4C particles to break. Also, with further increase of the milling time, the distance between B_4C particles decreased gradually and dispersed throughout the Al alloy matrix with a better homogeneity (Fig. 6c). The changed particle distribution continues up to steady-state condition (10 h, Fig. 6d) and at this condition, the increase of the milling time does not change significantly the distribution. These results demonstrate that the mechanical alloying process provides a homogeneous reinforcement particle distribution, which cannot be achieved using a conventional powder metallurgy process as reported in previous studies [26–28]. Zhao et al. [27] investigated the microstructural changes of the powder particles and the influence of the mechanical alloying on the distribution of SiC_p reinforcement, and their corresponding properties. They concluded that a relatively homogeneous distribution of SiC_p reinforcement in the matrix can be obtained by mechanical alloying technique when the rotational speed at 400 r/min for 5 h was reached. Parvin et al. [28] studied the effect of mechanical alloying on the physical and mechanical properties of SiC -reinforced Al6061 composites. They reported that the evolution of relative density and hardness with the milling time is due to the morphological and microstructural changes imposed on the composite powder. According to their results, a homogenous distribution of the 10 wt% SiC reinforcement particles in Al6061 matrix was successfully prepared using mechanical alloying technique.

Fig. 5 Iteration dependent error variation graphic of the ANN

4.2 Effects of the Compact Pressure and Milling Time on the Porosity

Compressive stress was applied on the powder particles, which were in contact with the punch during uniaxial compaction. These particles transmitted the stress to their neighbor particles, through the contact point. In an ideal model of the spherical and equiaxed particles, symmetrical opposite forces appeared in the contact points, which promoted the compressive deformation of the particles. The irregular morphology of the particle propitiated the formation of asymmetrically opposite forces in the contact points between the particles, which resulted in shear

Table 2 Validation data and predicted output from the ANN network for the validation data set

Sample ID	Compact pressure (MPa)	Reinforcement ratio (%)	Reinforcement size (μm)	Milling time (h)	Density (g/cm^3)			Porosity (%)		
					Measured	Predicted	Error (%)	Measured	Predicted	Error (%)
2	200	0	0	0.5	2.659	2.654	0.19	5.04	4.948	1.82
8	200	5	49	0	2.658	2.668	−0.38	4.6	4.452	3.22
11	200	5	49	2	2.622	2.616	0.23	5.89	6.225	−5.69
13	200	5	49	7	2.571	2.567	0.17	7.72	7.946	−2.92
16	200	10	49	0.5	2.595	2.590	0.20	6.39	6.439	−0.77
20	200	10	49	7	2.465	2.463	0.10	11.08	11.137	−0.52
26	200	20	49	5	2.511	2.492	0.75	8.49	9.228	−8.70
30	200	5	5	0.5	2.633	2.638	−0.19	5.49	5.502	−0.22
34	200	5	5	7	2.562	2.559	0.13	8.04	8.230	−2.36
38	200	10	5	1	2.572	2.565	0.27	7.22	7.263	−0.60
42	200	10	5	10	2.438	2.447	−0.35	12.05	11.768	2.34
47	200	20	5	5	2.473	2.477	−0.17	9.88	9.756	1.26
55	400	0	0	7	2.66	2.646	0.52	5	5.167	−3.34
59	400	5	49	1	2.681	2.681	−0.01	3.77	3.991	−5.86
61	400	5	49	5	2.647	2.649	−0.09	4.99	5.054	−1.28
63	400	5	49	10	2.615	2.612	0.10	6.14	6.343	−3.31
67	400	10	49	2	2.615	2.622	−0.28	5.66	5.418	4.27
70	400	10	49	10	2.503	2.511	−0.30	9.7	9.652	0.49
73	400	20	49	1	2.59	2.589	0.04	5.62	5.721	−1.79
78	400	5	5	0	2.702	2.706	−0.15	3.02	3.119	−3.29
81	400	5	5	2	2.668	2.669	−0.03	4.24	4.423	−4.31
86	400	10	5	0.5	2.632	2.631	0.02	5.45	4.984	8.55
93	400	20	5	0.5	2.591	2.595	−0.14	5.58	5.521	1.05
97	400	20	5	7	2.45	2.459	−0.36	10.71	10.356	3.30
100	600	0	0	0.5	2.754	2.747	0.24	1.64	1.677	−2.28
103	600	0	0	5	2.705	2.699	0.21	3.39	3.303	2.57
106	600	5	49	0	2.745	2.752	−0.26	1.47	1.504	−2.34
109	600	5	49	2	2.705	2.713	−0.30	2.91	2.870	1.38
111	600	5	49	7	2.667	2.673	−0.21	4.27	4.236	0.78
114	600	10	49	0.5	2.715	2.712	0.12	2.06	2.104	−2.12
121	600	20	49	0.5	2.661	2.668	−0.28	3.02	2.714	10.13
124	600	20	49	5	2.592	2.599	−0.28	5.54	5.360	3.25
128	600	5	5	0.5	2.73	2.733	−0.11	2.01	2.175	−8.19
132	600	5	5	7	2.655	2.665	−0.37	4.7	4.505	4.16
136	600	10	5	1	2.692	2.689	0.10	2.89	2.869	0.74
140	600	10	5	10	2.606	2.588	0.68	6	6.783	−13.05
145	600	20	5	5	2.582	2.593	−0.41	5.9	5.602	5.06
MAPE					0.119			1.720		
RMSE					0.005			0.179		

deformation decreasing in the compaction pressure for powder packing [29, 30].

It is known that the compaction mechanism of the powders in a rigid die is usually considered in three stages including (1) sliding and rearrangement of the particles; (2) elastic deformation of ductile powders and fragmentation

of brittle solids; (3) plastic deformation of bulk compacted powders. At the first stage of the compaction process, the particle sliding and rearrangement of the powders are the dominant mechanism of consolidation. When the applied pressure increases, the movement of the particles is restricted and the energy applied to the powder compact is

Fig. 6 SEM images of the Al2024-10 wt% B₄C composites after different milling times: **a** 0 h-conventional powder metallurgy, **b** 1 h, **c** 2 h, **d** 10 h

generally spent through the process of fragmentation and plastic deformation of the powders [31].

For a short milling time, higher value of the density is observed, indicating that the irregular morphology of the particle provides a higher deformation capacity during powder compacting, which dominates the work hardening due to the deformation imposed on the previous milling process. The density decreases with increasing milling time due to a dual effect, one is related to the powder morphology, which transformed from flattened to equiaxed and the other is related to greater work hardening due to the longer milling time. As a result, the porosity of the compacts increases as the milling time increases due to the hardening effect of the mechanical alloying (Fig. 7a). This can be attributed to the hardening effect of the mechanical alloying process, which increased the hardness of the powder particles and consequently limited the plastic deformation response of the aluminum. However, the porosity of the compacts decreases with increasing compression pressure due to the good packing and increasing density of metal powders (Fig. 7b) [32–34]. Hesabi et al.

[32] studied the densification response of aluminum powder reinforced with 5 vol% nanometric alumina particles (35 nm) during uniaxial compaction in a rigid die. They emphasized that the plastic deformation capacity of the milled composite powder was found to be less than that of the blended powder, showing the effect of distributed nanoparticles on the work-hardening rate and the hardness of the aluminum matrix. Zafarani et al. [33] studied the fabrication of PTFE–Hydroxyapatite composite by powder metallurgy and hot pressing method. They stated that an optimum fraction of hydroxyapatite (20 wt%) was found in which the best wear resistance was achieved. Gan and Gu [34] investigated the relation between the powder morphology and the compressibility of the Cu/SiC_p composite powder as a function of the milling time. They stated that the morphology and hardening effect during ball milling have an important influence on the compressibility of the powders. Moreover, they reported that the green density of the compacts decreased while the milling time increased due to the hardening effect of mechanical milling.

Fig. 7 The change of porosity with milling time and compaction pressure for unreinforced Al2024 alloy (a) and Al2024-20 wt% B₄C (D50:49 μ m) (b) composite

Fig. 8 The variation of the porosity with B₄C particle content and size

4.3 Effects of the Reinforcement Size and Ratio on the Porosity

Figure 8 shows the compressibility curves of Al–Cu–Mg/B₄C composite powders under different reinforcement ratios (wt%), the reinforcement sizes, and the compact pressures. Experimental results indicate that at the presence of B₄C ceramic particles the consolidation ability decreases depending on reinforcement ratio and size. The addition of B₄C particles decreased the consolidation of Al–Cu–Mg matrix, and the effect was more pronounced at higher B₄C content. Decreasing the size of B₄C particles also decreased compressibility (Fig. 8). The reinforcement particles are non-deformable and support a part of the applied pressure elastically. In fact, the effective pressure on the plastic phase is reduced. On the other hand, reinforcement clustering and the need for extra deformation of

the soft particles to fill the gaps between the contact points of hard particles decrease compressibility. This situation is particularly effective when long-range networks of reinforcement exist [18]. It is also feasible that agglomeration regions by formed coarse or fine B₄C particles restrict the movement of Al–Cu–Mg alloy particles, preventing the rearrangement of densification. When the relative size of B₄C particles decreases, it is more difficult for the soft matrix to fill the voids between the hard particles. These results have been observed in previous investigations [19, 23, 29].

4.4 Prediction Capacity of the ANN

The predicted values and errors for the density and porosity are provided in Tables 1 and 3. The ANN was tested using the test values (Table 3) selected from the experimental results that were not used during the learning processes. In most cases, the neural network prediction is very close to the actual value. However, several values are not as close as others. This is due to the errors caused by the materials, the measurements, and the process parameters. However, these errors could be neglected implying the learning level of the ANN is 98.4%. This study revealed that the predictions made using the ANN produced more accurate results.

Figures 9, 10, 11, 12 show the relationship between the real and calculated values obtained using the prediction models. The comparative plots of these values are provided in Figs. 11 and 12. The MAPE was used to evaluate the performance of the proposed ANN as a prediction technique. The MAPE were 0.126% for density and 1.625% for porosity. With respect to the results obtained from the plots of the ANN prediction, the highest MAPE value of 1.625%

Table 3 Experimental data and predicted output from the ANN network for the testing data set

Sample ID	Compact pressure (MPa)	Reinforcement ratio (%)	Reinforcement size (μm)	Milling time (h)	Density (g/cm^3)			Porosity (%)		
					Measured	Predicted	Error (%)	Measured	Predicted	Error (%)
4	200	0	0	2	2.634	2.627	0.28	5.9	5.849	0.87
6	200	0	0	7	2.612	2.604	0.32	6.71	6.658	0.78
12	200	5	49	5	2.594	2.602	−0.32	6.9	6.699	2.91
15	200	10	49	0	2.615	2.610	0.17	5.67	5.694	−0.42
18	200	10	49	2	2.572	2.562	0.40	7.22	7.454	−3.24
21	200	10	49	10	2.45	2.454	−0.15	11.62	11.559	0.53
24	200	20	49	1	2.542	2.535	0.27	7.36	7.619	−3.52
29	200	5	5	0	2.652	2.656	−0.15	4.81	4.871	−1.27
32	200	5	5	2	2.613	2.612	0.05	6.21	6.372	−2.62
37	200	10	5	0.5	2.58	2.581	−0.04	6.93	6.709	3.19
40	200	10	5	5	2.533	2.518	0.60	8.63	9.097	−5.41
46	200	20	5	2	2.51	2.531	−0.83	8.53	7.817	8.36
48	200	20	5	7	2.402	2.409	−0.28	12.47	12.153	2.54
52	400	0	0	1	2.693	2.690	0.13	3.82	3.702	3.10
56	400	0	0	10	2.657	2.640	0.65	5.11	5.391	−5.50
66	400	10	49	1	2.638	2.631	0.27	4.94	5.039	−2.00
68	400	10	49	5	2.592	2.593	−0.05	6.49	6.569	−1.22
74	400	20	49	2	2.578	2.580	−0.06	6.05	6.074	−0.39
76	400	20	49	7	2.471	2.468	0.11	9.95	10.026	−0.76
82	400	5	5	5	2.635	2.642	−0.28	5.42	5.296	2.28
84	400	5	5	10	2.605	2.605	0.01	6.5	6.610	−1.69
88	400	10	5	2	2.603	2.614	−0.43	6.1	5.681	6.88
90	400	10	5	7	2.505	2.514	−0.37	9.63	9.369	2.71
94	400	20	5	1	2.583	2.582	0.03	5.87	5.964	−1.61
98	400	20	5	10	2.437	2.442	−0.22	11.19	10.943	2.20
104	600	0	0	7	2.692	2.689	0.11	3.86	3.656	5.29
108	600	5	49	1	2.719	2.728	−0.32	2.4	2.364	1.50
113	600	10	49	0	2.722	2.723	−0.05	1.8	1.674	7.01
116	600	10	49	2	2.685	2.685	0.00	3.14	3.109	0.99
119	600	10	49	10	2.614	2.598	0.60	5.7	6.457	−13.28
122	600	20	49	1	2.653	2.651	0.09	3.32	3.353	−0.99
127	600	5	5	0	2.735	2.746	−0.40	1.83	1.724	5.77
130	600	5	5	2	2.697	2.708	−0.42	3.19	3.045	4.55
135	600	10	5	0.5	2.709	2.703	0.23	2.27	2.373	−4.54
138	600	10	5	5	2.653	2.657	−0.15	4.29	4.179	2.59
142	600	20	5	0.5	2.65	2.653	−0.12	3.43	3.304	3.67
146	600	20	5	7	2.515	2.524	−0.37	8.35	8.005	4.13
MAPE					0.126			1.625		
RMSE					0.006			0.179		

demonstrates that the network effectively generates sensitive results.

The comparisons of the measured and predicted (ANN) density, and porosity, at the testing stage are provided in Figs. 11 and 12. From these charts, it can be observed clearly that the ANN is properly trained and shows consistency in

predicting the properties of the composite. Comparisons between the measured and predicted composite properties at the testing stage indicate a high correlation. In other words, the results of the comparison plots indicate the similarities between the experimental study and the ANN model, and support the reliability of the model. The comparison

Fig. 9 Regression analysis for the neural network responses and the target for training data set: **a** density, **b** porosity

Fig. 10 Regression analysis for the neural network responses and the target for testing data set: **a** density, **b** porosity

Fig. 11 The comparison of measured values and ANN values for the density: **a** training data set, **b** testing data set

diagrams reveal that the slope and intercept of the regression equations for the outputs are very close to 1 and 0, respectively. The regression curves of the output variables for the

experimental and ANN datasets are shown in Figs. 9 and 10. The correlation coefficient was calculated to be 0.98 (testing, $R_{\text{density}} = 0.99495$, $R_{\text{porosity}} = 0.995567$, $R_{\text{hardness}} =$

Fig. 12 The comparison of measured values and ANN values for the porosity: **a** training data set, **b** testing data set

0.99235; training, $R_{\text{density}} = 0.99741$, $R_{\text{porosity}} = 0.99722$) indicating good agreement between the experimental results and the model predication. The statistical results namely, the root-mean squared error (RMSE) and the MAPE, are within an acceptable range and meet the integrity of the ANN learning and testing stages. Thus, reasonable agreement between the predicted and experimental data supports the accuracy of the model.

5 Conclusions

- (1) The mechanical alloying technique is an effective processing technique for the particle-reinforced metal matrix composites, which has some advantages over the conventional P/M method. In this technique, the B_4C ceramic particles can be distributed uniformly within the matrix alloy.
- (2) The porosity of the compacts increases with increasing the milling time due to the hardening effect of the mechanical alloying.
- (3) The porosity of the compacts decreases with increasing compression pressure due to the good packing and the increase in the density of the metal powders.
- (4) The compressibility of the composite powder mixtures is decreased when increasing the B_4C content. Therefore, the highest porosity value is observed in the powder mixture containing 20 wt% of B_4C particles.
- (5) The compressibility of the composite powder mixtures is decreased when the B_4C decreases in size. The agglomeration regions restrict the movement of Al–Cu–Mg alloy particles, preventing the rearrangement of densification.

- (6) ANNs can be an alternative approach for the evaluation of the density and porosity values of synthesized metal matrix composites. It was shown that experimental variables such as milling time, compact pressure, reinforcement size, and reinforcement ratio could be employed as inputs for predicting density and porosity values of synthesized composite materials.
- (7) The MAPE for predicted values does not exceed 1.625%. Therefore, using ANN values, satisfactory results can be estimated rather than measured which reduces the testing time and cost. Moreover, the ANN is an alternative method for estimating the properties of the metal matrix composites produced by the mechanical alloying method.

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