Original Article

Artificial neural network technique to predict the properties of multiwall carbon nanotube-fly ash reinforced aluminium composite

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**Abstract**

In this study, prediction of density and hardness properties using artificial neural network (ANN) and micro structural evolution of multi walled carbon nano tubes (MWCNT) and fly ashes (FA)/Al composites produced by powder metallurgy were investigated. The influence of content (wt. %) of reinforcements(MWCNTs and FA), ball milling time and sintering time on the mechanical properties were experimentally determined by measuring density and hardness values which are the outputs obtained from the artificial neural network. It was found that amount of reinforcements, ball milling time and sintering time play a major role in dispersion and enhancement of the properties. It was also demonstrated that ANN model is a powerful prediction technique to predict the mechanical properties of the composites. Blend powder morphology and sintered composite structure were investigated by scanning electron microscope (SEM). It was found that reinforcements were well dispersed for prolonged ball milling time and sintering time.

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1. Introduction

Aluminium is one of the popular metals used extensively in many engineering domains which include aerospace, automobile applications due to its low weight, high thermal conductivity and good corrosion resistance properties [1]. However due to the limitations of not possessing high strength to weight ratio properties, composite materials are preferred over pure aluminium. It is attractive to use aluminium based metal matrix composites (AMMCs) in aerospace, automobile and structural applications because of their high strength-to-weight and stiffness to weight ratios. However, the main drawback of AMMCs is their costly fabrication methods [2]. Fabrication of AMMCs can be accomplished through many techniques such as conventional casting or stir-casting [3–5], powder metallurgy [6,7], spray deposition [8] and diffusion bonding [9]. Because of the low processing temperature avoiding undesirable phases and dispersion of uniform reinforcement’s powder metallurgy is more preferred alternative than conventional method. In powder metallurgy method powders of metal matrix and reinforcements are blended to
achieve homogenous mixture and then compressed to the required shape. After compaction, sintering process is carried out to get better mechanical properties [7].

Ball milling is a useful powder metallurgy dispersion method that can lead to the homogeneous dispersion of reinforcements in the metal matrix [10]. Many researchers have demonstrated that ball milling is one of the effective dispersion methods in powder metallurgy to disperse the hard reinforcements such as silicon carbide [11], aluminium oxide [12], CNTs [13], Fly ash [14]. The reinforcements such as flyash, silicon carbide, aluminium oxide and CNTs have been extensively tried out in aluminium matrix composites to enhance mechanical and wear properties. Esawi et al. [15] observed improved mechanical properties of the composites due to CNT content prepared by ball milling. Perez-Bustamante et al. [16] reported ball milling time and the content of MWCNTs have predominant influence on the mechanical properties of the of aluminium based nanocomposites reinforced with MWCNTs prepared by mechanical milling with pressure-less sintering at 823 K under vacuum. The Kwon et al. [17] reported that a small addition of 5 vol% CNTs in Al–CNT composites fabricated by nanoscale dispersion method and spark plasma sintering followed by hot extrusion elevated the strength to about thrice that of pure aluminium. Wang et al. [18] found improved properties of CNT-dispersed aluminium matrix composites fabricated by powder metallurgy routes. Selvam et al. [18] fabricated AA6061/fly ash AMCs by compocasting method and reported that the incorporation of fly ash particles enhanced the microhardness and tensile strength of the AMCs. Mejtafh Hrairi [19] developed A356–fly ash metal matrix composites by Powder metallurgy and found improved properties. Marin [20] found that FAs addition into the Al matrix increases mechanical properties and hardness with respect to pure sintered aluminium.

In the field research prediction technique plays an important role, this will reduce the number of experiments that needs to be conducted by providing correlation between input and output. The conventional statistical prediction approach will provide satisfactory response but their performance will reduce when given data is highly nonlinear. Also it requires large number of sample and less number of input features in a given training data set in order to generate best correlation. But in composite material, performing huge number of experiment is time consuming and expensive. To overcome these limitations, a non-linear statistical model known as artificial neural network (ANN) is widely used [21]. This is a computational algorithm with function & structure inspired by biological neural network. Learning capability of this algorithm made it popular in the field of research. Artificial neural network, an artificial intelligence modelling technique is a supervised learning algorithm. Artificial neural network is a reliable prediction technique and can be successfully employed in prediction of mechanical properties composites [22–29].

The final properties of the bulk composite depend on the content (wt.%) of reinforcements, size of particles and their processing history. Therefore content of reinforcements (wt.% FA and wt.% of MWCNT), sintering time and ball milling time were selected as the input parameter in this study. These control parameters have non-linear relationship with density and hardness properties which are the outputs obtained from the proposed artificial neural network. The purpose of this work therefore, was to: (a) find the effect of content of reinforcements, ball milling time and sintering time on the density and hardness properties of MWCNT and FA reinforced aluminium matrix composites; (b) develop the artificial neural network model in order to predict the influence of control parameter on density and hardness properties; and (c) to study the microstructure of blend powder morphology and sintered composite to analyse the distribution of reinforcements.

### 2. Experimental procedure

In this study, pure aluminium powder used as matrix (specification: 99.7% pure, 200 mesh) 4, 8 and 16 wt% of Fly Ashes (specification: precipitator type 50 μm) and 0.25, 0.5 and 0.75 wt.% multi-wall carbon nanotubes (specification: outer diameter – 10 nm–15 nm and inner diameter 2–6 nm and 0.1–10 μm length, Chengdu chemicals co. ltd.) are used as reinforcements. The powders are ball milled with stainless steel balls using a Planetary-ball milling machine at 250 rpm. The ball-to-powder weight ratio of 8:1 and milling time is set for 1, 2 and 4 h. The 3 wt.% methanol is added into the powder blend as a process control agent to prevent cold welding. 15 g of the ball-milled powders are cold compacted in a cylindrical die of 12 mm diameter at 285 MPa followed by argon inert gas sintering at 500 °C for sintering time of 1, 3 and 6 h. Density of the composites was evaluated by the Archimedes principle [21]. The relative density of the specimen is calculated from the following equation:

\[
\text{Relative density} = \left( \frac{\rho_c}{\rho_{ct}} \right) \times 100
\]  

(1)

where, \( \rho_{ct} \) is the theoretical density, \( \rho_c \) is the actual density, If \( \rho_w \) is density of the distilled water and \( m_1, m \) = the weight of composite specimen in water and air respectively, the actual density of the composite \( \rho_c \) can be evaluated from the following equation [21]:

\[
\rho_c = \frac{m}{m_1 - m} \times \rho_w
\]  

(2)

Theoretical density \( \rho_{ct} \) was evaluated based on the rule of mixture [21].

\[
\rho_{ct} = V_{AI} \rho_{AI} + V_{FA} \rho_{FA} + V_{CNT} \rho_{CNT}
\]  

(3)

where \( \rho_{AI}, \rho_{FA} \) and \( \rho_{CNT} \) are densities of the pure aluminium (2.8 g/cm³), fly ash (1.87 g/cm³) and the multi walled carbon nanotubes (2.1 g/cm³), respectively. By means of scanning electron microscopy (SEM) the blend powder morphology and sintered composite were investigated. The macro hardness the composites was evaluated using Vickers hardness testing machine. The average of five readings was considered for the each sample.
3. Artificial neural network modelling technique

Artificial neural network (ANN) an artificial intelligence modelling technique is a supervised learning algorithm. It has several nodes interconnected with one another and known as neurons. The neurons are the processing unit in this algorithm arranged in different layers in neural net. Feed forward control neural net is the simple and most commonly used neural network in ANN, it has no cyclic connection between unit and nodes of network. The information given at input flows in one direction via hidden layer to output layer as shown in Fig. 1.

3.1. Artificial neural network training and testing

Artificial neural network was used to predict hardness and relative density using ‘ntool’ in MATLAB software package. In this study a feed-forward back propagation algorithm with training function (trainlm) and adaption learning function (learnngdm) were used in the prediction. Fig. 2 shows artificial neural network with four hidden layer and 4 neurons. The fly ash content (FA), multi walled carbon nanotube content (CNT), sintering time (ST), ball milling time (BM) time were used as the input parameters while the relative density and hardness (VHN) were employed as a target or output value in the artificial neural network models. Both input experimental data and target values were used to train the ANN algorithm. To avoid biased response normalizing operations were carried out toward maximum or minimum value of input data set using the following equation:

\[
N = \frac{X_i - \text{Maximum of } X}{\text{Maximum of } X - \text{Minimum of } X}
\]

where \( N \) is the normalized value, \( X \) is the training data set, \( X_i \) is the values of each input data in training set, \( i = 1, 2, 3, 4 \ldots \)

The normalized value lies (0, 1 range) and to obtain original value reverse normalization operations were carried out.

The performance of ANN model measured using two commonly error measuring statistical models, the mean absolute percentage error(MAPE) and the root mean squared error (RMSE). The values of MAPE and RMSE are calculated from Eqs. (5) and (6) [21].

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{T_i - P_i}{T_i} \right| \times 100
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (T_i - P_i)^2}
\]

where, \( n \) = Number of data points, \( T \) = Target value or Original value, \( P \) = Predicted value or Forecast value.

Experimental data sets of 81 samples of different levels and parameters were used to train ANN model as shown in the Table 1. Performance of trained model measured in terms of mean absolute percentage error (MAPE), root mean squared error (RMSE) and correlation factor (R). The correlation factor R was generated by MATLAB software package while MAPE and RMSE values were measured from Eqs. (4) and (5), respectively. The trials were carried out until correlation coefficient R approaches closer to the value one. It can be found that value of mean absolute percentage error (MAPE) for predicted relative density and hardness are 0.365% and 2.570% respectively. Similarly, root mean squared error (RMSE) value for predicted relative density and hardness are 0.409 and 1.023 respectively. The correlation factor R value close to one ensures better regression fit for given training set. Fig. 3 shows the value of the correlation factor R close to one thereby ensuring good training. Also it was found that both RMSE and MAPE values resulted in satisfactory values i.e. close to zero [21].

Table 1 – Levels of input parameters for MWCNT and FA/Al composite.

<table>
<thead>
<tr>
<th>FA (wt.%)</th>
<th>CNT (wt.%)</th>
<th>Ball milling time (h.)</th>
<th>Sintering time (h.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.25</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>0.5</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>16</td>
<td>0.75</td>
<td>4</td>
<td>6</td>
</tr>
</tbody>
</table>

Fig. 1 – Typical Feed forward neural network schematic representation.

Fig. 2 – Input and output parameters for training ANN.
4. Results and discussion

4.1. Microstructure study

Fig. 4(a–c) shows the micrographs of the blended powders for ball milling time of 1, 2 and 4 h, respectively. It can be seen that 1 h ball milling time results in cold welding of mixture particles leading to increase of the particle size. As the milling time is increased from 1 h to 4 h, work-hardening of the powders is increased which tends to fracturing more particles than cold welding leading to a refinement in the particle size [14]. It is clear that 1 h ball milling leads less damage of MWCNT & Fly ash particles but comparatively poor homogeneous mixture while 4 h ball milling results more damage in reinforcements but comparatively homogenous mixture. Liu et al. also observed a shape change from flake-like structure to more or less granular structure of the mixture particles as ball-milling time increased, because a dynamic equilibrium attained between fracturing and agglomeration. It is clear from the Fig. 4 that CNTs-FAAs were gradually dispersed into the aluminium matrix powders as ball milling time increased to 1–4 h. At 1 h ball-milling time, CNT clusters were adhered to the surfaces of the Al powders and homogenous incorporation of Fly ash particles into the aluminium powders (Fig. 4a). When increasing the ball-milling time to 2 h, CNTs clusters were decreased on the Al surface and reduction in FA clusters destroying the spherical structures (Fig. 4b). After 4 h ball milling time, very less CNTs clusters were adhered on the Al surface indicating that most of the CNTs were dispersed into the aluminium powders and also further reduction in the FAs clusters was observed (Fig. 4c).

4.2. Mechanical properties

The relative density and hardness tests showed that both relative density and hardness were decreased for 4 h ball milling time compared to 2 h. This was because 4 h ball milling resulted in serious damage to the CNTs and FA. At 4 h ball milling, more mixture powders were fractured and exhibited an irregular shape increasing the porosity level and decreasing the ductility of the aluminium matrix. These conditions would decrease the relative density and hardness properties of the composites [6].

4.3. Influence MWCNT, FA, ball milling time, and Sintering time on the relative density property

Figs. 5(a), 6(a) and 7(a) shows the influence MWCNT, FA, ball milling time, and sintering time on the relative density property. Only selective graphs have been plotted due to the similarities in the trend. It can be noted that relative density of composite tends to decrease with increase in MWCNT and FA content due to the low density of MWCNTs and FAs. It can also be noted that increase in ball milling time had no effect on relative density and remained constant for all variation of ball milling time while increase in the sintering time increases the relative density. This incremental effect may be due to the good adhesion of aluminium matrix and reinforcements leading to reduction in porosity.

4.4. Influence MWCNT, FA, Ball milling time, and Sintering time on the hardness property

Figs. 5(b), 6(b) and 7(b) shows the influence MWCNT, FA, ball milling time, and sintering time on the hardness property. Only selective graphs have been plotted due to the similarities in the trend. It can be noted that hardness of the composite decreases with the increase in MWCNT content due to the agglomeration of MWCNTs while increase in fly ash content increases hardness of the composite up to 8 wt.% and then falls with further addition of fly ash. Increment of hardness can be attributed to the harder fly ash particles while decrement of hardness can be attributed to the high porosity in
Fig. 4 – Micrographs of the blended powders at BM speed 250 rpm and BM time (a) 1 h, (b) 2 h, (c) 4 h.

Fig. 5 – Effect of sintering time, wt.% of CNTS and FAs on (a) relative density, (b) hardness for ball milling time 1 h.
Fig. 6 – Effect of sintering time, wt.% of CNTS and FAs on (a) relative density, (b) hardness for ball milling time 2 h.

Fig. 7 – Effect of sintering time, wt.% of CNTS and FAs on (a) relative density, (b) hardness for ball milling time 4 h.

Table 2 – ANN Predicted values of unseen data of 20% Fly ash and 0.25 wt.% CNT.

<table>
<thead>
<tr>
<th>FA (wt.%)</th>
<th>MWCNT (wt.%)</th>
<th>Sintering time (h)</th>
<th>Ball milling time (h)</th>
<th>Relative density (%)</th>
<th>VHN</th>
<th>Predicted relative density (%)</th>
<th>Predicted VHN</th>
<th>APE of relative density</th>
<th>APE of VHN</th>
<th>Squared error of relative density</th>
<th>Squared error of VHN</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.25</td>
<td>1</td>
<td>2</td>
<td>86.64</td>
<td>25.1</td>
<td>86.4957</td>
<td>23.709</td>
<td>0.16</td>
<td>5.539</td>
<td>0.021</td>
<td>1.933</td>
</tr>
<tr>
<td>20</td>
<td>0.25</td>
<td>1</td>
<td>4</td>
<td>86.26</td>
<td>23.06</td>
<td>86.5454</td>
<td>23.835</td>
<td>0.33</td>
<td>3.362</td>
<td>0.081</td>
<td>0.601</td>
</tr>
<tr>
<td>20</td>
<td>0.25</td>
<td>3</td>
<td>1</td>
<td>85.87</td>
<td>23.42</td>
<td>86.8016</td>
<td>25.163</td>
<td>1.08</td>
<td>7.443</td>
<td>0.868</td>
<td>3.039</td>
</tr>
<tr>
<td>20</td>
<td>0.25</td>
<td>3</td>
<td>2</td>
<td>87.03</td>
<td>27.47</td>
<td>86.8372</td>
<td>25.271</td>
<td>0.22</td>
<td>8.003</td>
<td>0.037</td>
<td>4.833</td>
</tr>
<tr>
<td>20</td>
<td>0.25</td>
<td>3</td>
<td>4</td>
<td>86.26</td>
<td>26.33</td>
<td>86.9133</td>
<td>25.501</td>
<td>0.75</td>
<td>3.146</td>
<td>0.427</td>
<td>0.666</td>
</tr>
<tr>
<td>20</td>
<td>0.25</td>
<td>6</td>
<td>1</td>
<td>86.26</td>
<td>24.31</td>
<td>86.7852</td>
<td>25.252</td>
<td>0.60</td>
<td>3.879</td>
<td>0.276</td>
<td>0.889</td>
</tr>
<tr>
<td>20</td>
<td>0.25</td>
<td>6</td>
<td>2</td>
<td>87.42</td>
<td>27.59</td>
<td>86.8225</td>
<td>25.370</td>
<td>0.68</td>
<td>8.043</td>
<td>0.357</td>
<td>4.925</td>
</tr>
<tr>
<td>20</td>
<td>0.25</td>
<td>6</td>
<td>4</td>
<td>87.03</td>
<td>26.61</td>
<td>86.9028</td>
<td>25.621</td>
<td>0.14</td>
<td>3.713</td>
<td>0.016</td>
<td>0.976</td>
</tr>
</tbody>
</table>

VHN, Vickers hardness number; APE, Average percentage error; MAPE, mean absolute percentage error; RMSE, root mean squared error (RMSE).
the composites containing high content of fly ash particles. Increase in ball milling time increases hardness up to 2 h and then falls with further increase in ball milling time. Increment of hardness can be attributed to the ability of attaining the homogenous mixture of powder particles during ball milling. Decrement in hardness may be attributed to the strain hardening of reinforcement particles. It can be also shown that increase in sintering time increases the hardness. This incremental effect may be due to the good adhesion of aluminium matrix on reinforcing materials as sintering time increases.

4.5. Prediction of mechanical properties using artificial neural network (ANN)

The main quality indicator of a neural network is its generalization ability, its ability to predict accurately the output of unseen data and this is achieved by validating dataset. After developing training model, the simulation was carried out for the prediction of the values for 20 wt.% FA and 0.25 wt.% CNT. Table 2 shows the predicted values along with experimental values and eventually performance of the prediction measure. The mean absolute percentage error (MAPE) of relative density and hardness were found to be 0.14 & 1.597, respectively, while root mean squared error (RMSE) of relative density and hardness were found to be 0.278 and 0.814 respectively. The small magnitude of RMSE and MAPE concludes good prediction accuracy can be employed in prediction of mechanical properties composite [21].

5. Conclusion

Aluminium metal matrix composites reinforced composites with 0.25, 0.5 and 0.75 wt.% multi wall carbon nano tubes (MWCNTs) and 4, 8 and 16 wt.% fly ashes (FAs) were successfully developed by powder metallurgy technique. Powder morphology, density, hardness properties of the specimens were investigated. Influence of content of reinforcements, ball milling time and sintering time on the hardness, density properties of the MWCNT and FA reinforced Al composites were systematically analysed. Artificial neural network (ANN) analysis was used to predict the hardness and density properties.

Following conclusions were drawn from the study.

1) In this study it was found that increase in MWCNT content decreased hardness whereas increase in FA content increased hardness up to 8 wt.% and then decreased, increase in 2 h ball milling time increased hardness and then decreased and increase in sintering time increased hardness.
2) Increase in MWCNT content and FA content decreased density, however density remained constant for the increase in ball milling time but density increased with increase sintering time.
3) The result also indicated that composite 0.25 wt.% CNT - 8 wt.% FA/Al with 2 h ball milling and 6 h sintering time was the optimum combination of MWCNTs, FA and BM time that resulted in improved mechanical properties.
4) The SEM images of the blended powders and sintered composite indicated that CNTs and FA were homogeneously distributed.
5) ANN generated satisfactory output when compared with experimentally measured data. The performance of prediction measured by MAPE and RMSE, during validation was found that, for relative density MAPE = 0.14 and RMSE = 0.278, for Vickers hardness number MAPE = 1.597 and RMSE = 1.283.
6) The usefulness of ANN prediction technique in the field of composite material technology thrivingly demonstrated by predicting hardness and relative density properties. Therefore, properties can be estimated using ANN rather than measuring experimentally thereby reducing the testing time and cost.

Conflicts of interest

The authors declare no conflicts of interest.

REFERENCES


