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NUMERICAL PREDICTIONS OF THE MECHANICAL PROPERTIES OF A356-SIC COMPOSITES FABRICATED BY POWDER METALLURGY

Summary

Pure aluminum nanocomposite reinforced with silicon carbide was produced by powder metallurgy process. The mechanical behavior of this composite was modelled and experimentally investigated. Measurements of density, tensile properties, and hardness showed that the tensile strength and the porosity of composites increased with an increase in the amount of nanoparticles; however, aluminum ductility decreased. On the other hand, the elongation percentage remains constant with an increase in the percentage of nanoparticles. Wear resistance of composite samples was higher than that of aluminium alloy. In the current research, a technique based on Artificial Neural Network (ANN) and Finite Element Method (FEM) was applied for the prediction of mechanical properties. It was observed that prediction results obtained in this study are consistent with the real measurements performed on composites.

Key words: *nano SiC, finite element method, artificial neural network.*

1. Introduction

Today, aluminum-based composites are in demand because of their superior mechanical properties such as specific stiffness, high elastic modulus, good wear resistance and fatigue strength. These metal matrix composites have been considered as a good choicein the automobile and aerospace industries [1,2].There are different techniques for producing particle reinforced composites, such as liquid metal infiltration, spray decomposition, squeeze casting, powder metallurgy (PM) [3-5].

Powder metallurgy is a highly developed technique that consists of three steps: mixing of elements (powder), compacting those elements inside a metal die, and then heating the sample in a furnace to create a bond between the elements [6].

Tribological properties of aluminum matrix composites could be improved by using ceramic particles. A number of researchers have noticed that mechanical properties of the matrix alloy are improved by increasing the amount of reinforcing particles [7-10]. The wear in composite materials was found to be lower than in the matrix alloy; it was also found that the wear resistance increases with an increase in the percentage of reinforcing particles. This is because the hard particulates are wear and abrasion resistant and give protection to the surface [11].

Many researchers have been working on the dry sliding wear behavior and the mechanical and physical properties of aluminum matrix composites reinforced with different particulates, for example Al_2O_3, SiC, silica sand, boron, TiC, MgO, and Si_3N_4. They noticed that the reinforcement material improves the yield strength and the ultimate tensile strength of the metal. However, the ductility of aluminum metal composites deteriorates significantly with the highest concentration of ceramic particles. To protect the composites from the ductility deterioration, it will be suitable to produce cast lightweight components from nanocomposites with a uniform distribution of nano reinforcements [12–17].

Recent studies have found that the addition of 1.5 vol. % nano SiC particles to Al alloys resulted in mechanical properties that were practically identical to those of the Al alloy and surprisingly better than those of composites that have a high content of micro-sized particles.

Previous studies on the Al composites have reported that the particle size is related with the improvement in resistance to wear. Artificial Neural Network (ANN) was firstly introduced by Maureen Caudill, who suggested that the computational model has the ability to simulate the functions of the human brain. However, the ANN theory did not attract interest for a long time. In the last decades, numerous studies have shown that ANN architectures could be used in several aspects. The architecture of an ANNs is specified usually by the number of layers in the ANN model and by the number of the neurons in each layer [18–23]. As shown in Figure 1, the ANN model consists of an input, a hidden, and an output layer.

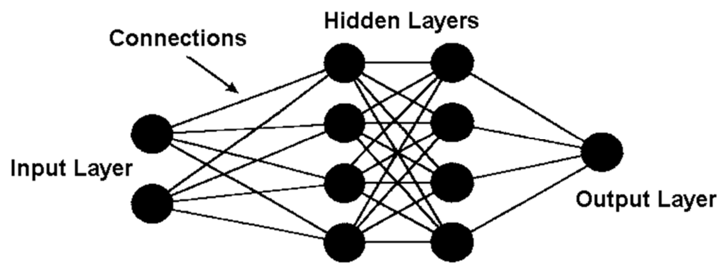

Fig. 1 Schematic of the neural network architecture.

In this study, the wear behavior and mechanical properties of Al-alloy (A356) matrices reinforced with different vol. % of nano ceramic (SiC) were investigated. The combination of FEM and the artificial neural network is used to predict these properties.

2. Experimental work

Pre-alloyed aluminum silicon (A356) powder supplied from the Al Nassr company in Egypt with the average grain diameter of 15 μm was used as a matrix. The chemical composition of A356 is shown in Table 1. Silicon carbide (SiC) particles with an average diameter of 50 nm were used as reinforcement. The preparation of nanoparticle reinforcements is described in a previous study [24]. Aluminum silicon (A356) powder was mixed with ceramic particles to prepare composites with about 0.5, 1.5, 3.5, and 4.5 vol. % reinforcement. The mixing process took place in a ball mill. The powder mixtures were compressed at room temperature for 6 minutes under a pressure of 104 N/cm^2 using a ram (H13 tool steel) into samples having dimensions of $150 \times 150 \times 150$ mm^3. The compact samples were sintered at 585 ºC in the argon gas atmosphere for one hour. Then, the samples were left to cool in the air and the temperature of samples was monitored by using a non-contact Temperature Sensor (PALIDA type). The compacts were quenched in water at 585, 485, 385, 285, and 185 °C.

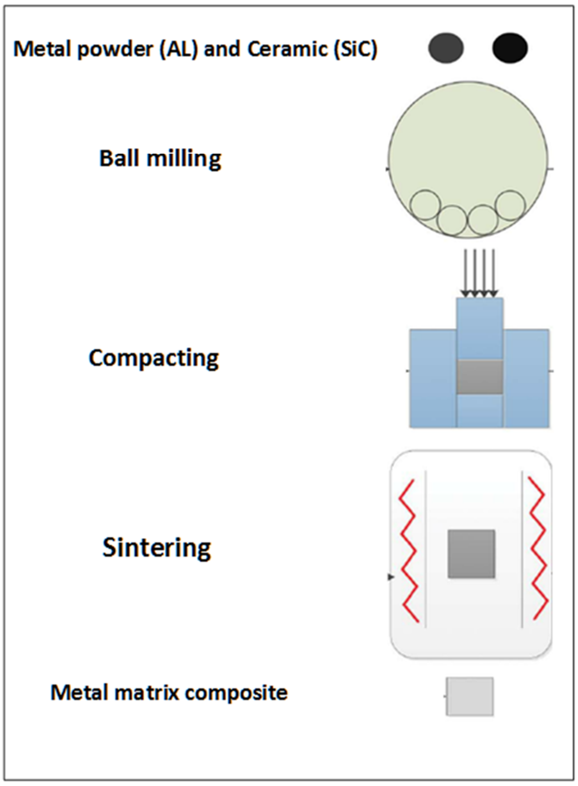

Fig. 2 Powder metallurgy production method

Table 1 Chemical composition of A356 alloy

Component	%
Aluminum, Al	91.1
Magnesium, Mg	0.25
Manganese, Mn	0.1
Silicon, Si	6.5

The density of the samples was obtained experimentally by Archimedes' method while the theoretical density was calculated by using a rule of mixtures at each temperature. The degree of porosity in the composite was calculated by comparing the theoretical density with the measured density. Tensile tests were carried out according to the ASTM standard E8 on a Lloyds testing machine to estimate tensile properties of the composites (yield strength and ultimate tensile strength). The Brinell hardness values were measured on polished samples at each volume % of nano SiC at a load of 30 N.The dry sliding wear experiments were conducted by using a pin-on-disc wear testing apparatus at different applied loads and at room temperature.The design of the pin-on-disc apparatus is described in a previous study [7]. Cylindrical samples with 12 mm in length and 8 mm in diameter were used in the wear test.

Table 2 Physical parameters

	Solid	Liquid
Heat diffusion coefficient	90	90
Density	2681	2396
Heat capacity	$C_{pS=}$ 965	$C_{pL=}$ 1082

Table 3 Boundary conditions in heat transfer

	Melt (T_M)	Solidus (T_S)	Liquidus (T_L)	Surrounding temperature (T)
Temperature /°C	700	557	613	25

Table 4 Thermal boundary condition

Thermal conductivity	0.00566 Calorie/cm C s
Temperature difference	560 °C
Distance	150 mm
Heat transfer rate	21.1344 calorie/cm^2 s

3. Finite Element Method (FEM) and Artificial Neural Network (ANN)

To predict mechanical properties of a composite, one has to determine the relationship between mechanical properties and solidification conditions after the sintering process. In this study, the mechanical behavior is considered to be related to the rate of cooling, gradient in temperature, and vol. % of SiC. Equation 1 is the general heat conduction equation for variable conductivity and the unsteady heat storage for a sintered sample having dimensions of 150 × 150 × 150 mm^3 [25].

$$\frac{\partial(k\partial T)}{\partial x(\partial x)}+\frac{\partial(k\partial T)}{\partial y(\partial y)}+\frac{\partial(k\partial T)}{\partial z(\partial z)}+q=\rho C_{\mathrm{p}}\frac{\partial T}{\partial t} \tag{1}$$

By using C_p, the method for removing q when k is constant,

$$C_{\mathrm{p}}=f_{\mathrm{s}}\cdot C_{\mathrm{ps}}+(1-f_{\mathrm{s}})\cdot C_{\mathrm{pL}}+\frac{L}{T-T_{\mathrm{S}}}\cdot f_{\mathrm{s}} \tag{2}$$

f_s is given by the Scheil equation at the temperature of T=585 ºC in the interval $T_S < T < T_L$ [25]:

$$f_{\mathrm{s}}=\left\{1-\left(\frac{T-T_{\mathrm{m}}}{T_{\mathrm{L}}-T_{\mathrm{m}}}\right)^{\frac{1}{k_0-1}}\right. \tag{3}$$

Based on the transient temperature model, the FEM is utilized for discretization and for determining the transient temperature field of quenching. Since it is almost at

$$T=T_{\mathrm{S}}+0.1\cdot(T_{\mathrm{L}}-T_{\mathrm{S}}) \tag{4}$$

that the latent heat and the final structure are obtained, the cooling rate and the temperature gradient are then calculated as follows:

$$\text{Cooling rate} \quad (\mathrm{R})=T_{(i,j,k,t)}-T_{(i,j,k,t+1)} \tag{5}$$

$$\text{Temperature gradient} \quad (\mathrm{G})=\left|T_{(i+1,j,k,t)}-T_{(I,j,k,t)}\right| \tag{6}$$

The application of ANN in the materials science engineering research has recently caught attention in the research literature [18-23, 25-29].

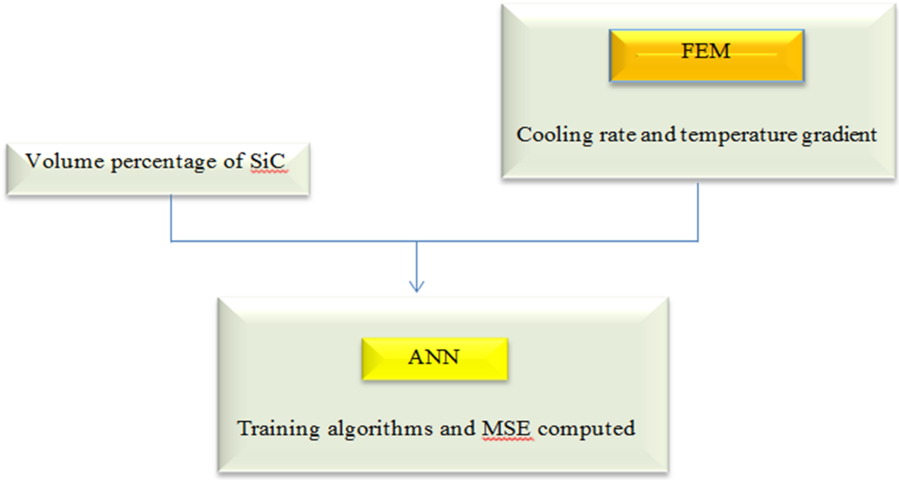

Fig. 3 Scheme of a FEM–ANN prediction model

4. Results and Discussion

4.1 Wear Test

Figure 4 shows the results of weight loss of the samples as a function of the applied load. It has been found that the wear resitance behavior of unreinforced alloy is lower than that of composites. This improved behavior is a result of the hard ceramic material which protects the surface [30–32]. The results given in Figure 5 show that the weight loss decreases as the percentage of the nano SiC particles increases from 0.5% to 4.5%. This is possible because the ceramic material on the composite surface protects the matrix from direct contact. Figure 4 also shows that when the applied load increases, the wear rate of all investigated samples increases. Conditions of heavy wear are clearly seen from the rate of weight loss. The recognized pattern is in agreement with that noted by Alpas and Zhang [32] who suggest that the wear rate increases gradually with the applied load in the mild wear region.

From Figure 6 we can see that the composites exhibit smaller amounts of weight loss than the matrix alloy.

The weight loss results show that no single wear mechanism operates over the wide range of the lost weight (0- 4.5%). Rather, there are several mechanisms, while the change in their relative importance depended on the varied vol. % of nano ceramic particles and the applied load (mechanical stress). The main factors controlling the importance of the underlying mechanisms are mechanical stress, temperature, oxidation phenomenon, and ceramic particle vol. %. Taking all these factors into consideration is essential for understanding the sliding wear of metals. It must also be notedthat the conditions of the interface may be very different, especially in terms of temperature and the surrounding environment. The complexity of sliding wear arises from the fact that all the factors are interrelated and may be influenced by both the tested material and the applied load in terms of the coefficient of friction between two sliding surfaces. The obtained results show that increasing the load leads directly to higher stresses, and this will result in more severe mechanical damage, especially to free ceramic particle samples. The main factor affecting the wear processes is the applied load. The load applied to the sample being tested is transmitted as the normal stress on the sample surface and the sheer stress below the worn surface. If the load is low enough or if the surface resists the load well enough, the wear process will proceed only very slowly. The associated plastic flow and maximum shear stress will take place beneath the material surface and the plastic strain accumulated by each sliding pass will be small.

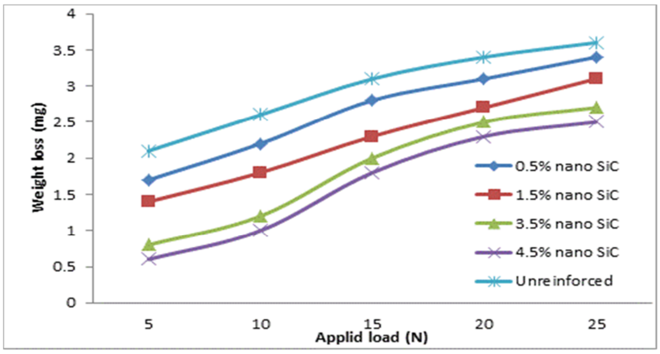

Fig. 4 Wear resistance at different applied loads

In general, composite materials have excellent wear resistance compared with the alloy regardless of the sliding speed and the applied load [20]. This result is predictable bearing in mind that, in general, harder materials have better wear resistance (Figure 5). This is because nano SiC particles act as an obstacle to the motion of dislocation [33,34]. Figure 6 shows that higher hardness was observed after the sample had been completely cooled. This is due to excellent bonding between the matrix and ceramic particles. The results indicate that lower hardness values at maximum temperatures occurred due to the relatively faster cooling rate, internal stress in the samples, and dislocation density. The high dislocation density in the composite material matrix causes a significant increase in the hardness value at 185 °C; this result is in agreement with the hardness measurements performed by Dutta et al., [35] on an A1-6061 composite with $A1_2O_3$ particles.

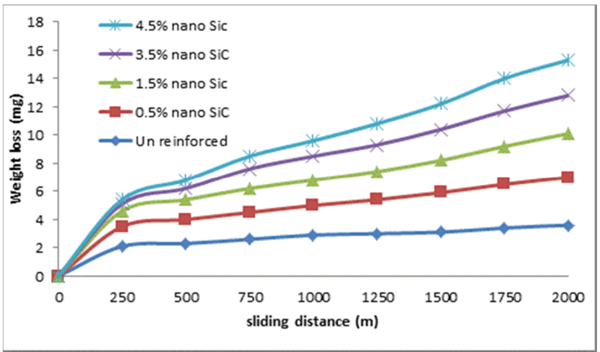

Fig. 5 Effect of sliding distance on the weight loss

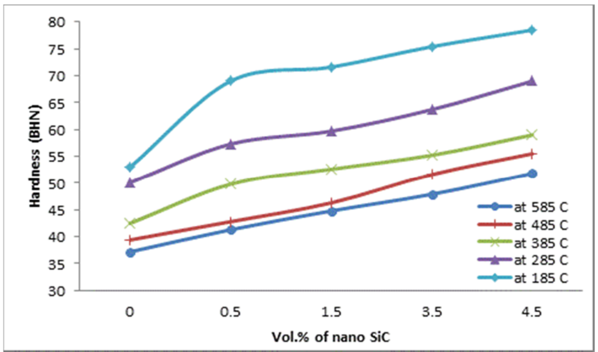

Fig. 6 Hardness as a function of vol % of nano SiC particles

4.2 Tensile Tests

Micron-sized particles are usually used to improve the metal tensile properties. However, the ductility of the composite deteriorates significantly with a higher concentration of ceramic particles [34, 36]. The stress-strain behavior of five samples was tested and the results are shown in Figure 7. The figure shows that ductility decreases with a further increase in the volume percentage of reinforcement. This could be due to the weak bonding between the matrix and the nano particles. It is clear that there are two factors influencing the tensile properties of composites:

1. The reinforcing particles increase the strength of the material by simple load transfer, which depends on the bond integrity at the particle/matrix interface and dislocation motion.
2. The inhibition of plastic relaxation at the particle/matrix interface [24]

The results show that the addition of nano SiC particles to A356 alloy matrix composites increases the strength of the alloy at room temperature continuously as the vol.% of SiC particles increases from 0.5 to 4.5. The measured maximum and minimum tensile strengths of the composite samples were found to be 252 and 200 MPa, respectively. The observed great enhancement in tensile strength is due to the good distribution of the nano ceramic particles (Figures 8 and 9), while the low degree of porosity results from using the powder metallurgy method that provides the uniform distribution of strong SiC particles. The great multi-directional grain refinement and the thermal stress at the aluminum /SiC interface are also very important factors which play a major role in improving the strength properties of the composite. Grain refinement has a strengthening effect on SiC particles because the particles act as a heterogeneous nucleation impetus for the matrix which is improved with an increase in the volume fraction [36].

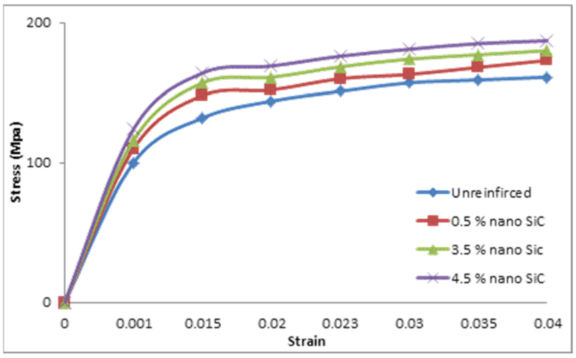

Fig. 7 Stress–strain behavior of the composites

According to the experimental results, a significant enhancement in strength is observed when nano particles are added; however, a further increase in the amount of SiC nanoparticles leads to a reduction in the strength values.This happens due to particle clusters and porosity. Figure 10 shows that porosity was reduced when the sample temperature dropped from 585 to 185 °C. The degree of porosity affects the tribological performance and mechanical properties. According to our results, the samples sintered at 185 °C had the best mechanical properties (tensile strength and hardness). That happened after the sample had been completely cooled by the effect of the reduction in the interfacial area between the ceramic particles and aluminium, leading to a lower degree of porosity.

4.3 Prediction of Mechanical Behavior of Metal Matrix Composites

The structure of the implemented neural network consists of a hidden layer, an output layer, and an input layer. In choosing a suitable multilayer perceptron (MLP) architecture one has to specify the function of activation and the required number of neurons in the hidden layer. The trial and error analysis resulted in the selection of a suitable activation function for each model. The selection of the number of hidden nodes in a multilayer perceptron is the most difficult and a very important step. The training algorithm process would take a lot of time to find the optimumones. Therefore, the behavior of error in a neural network must be observed in order to find it with a very high degree of accuracy. There is not a certain rule about how to choose the number of neurons in the hidden layer; it can be calculated by experiment. For the prediction of mechanical properties of a composite , a combination of FEM and ANN can be used.

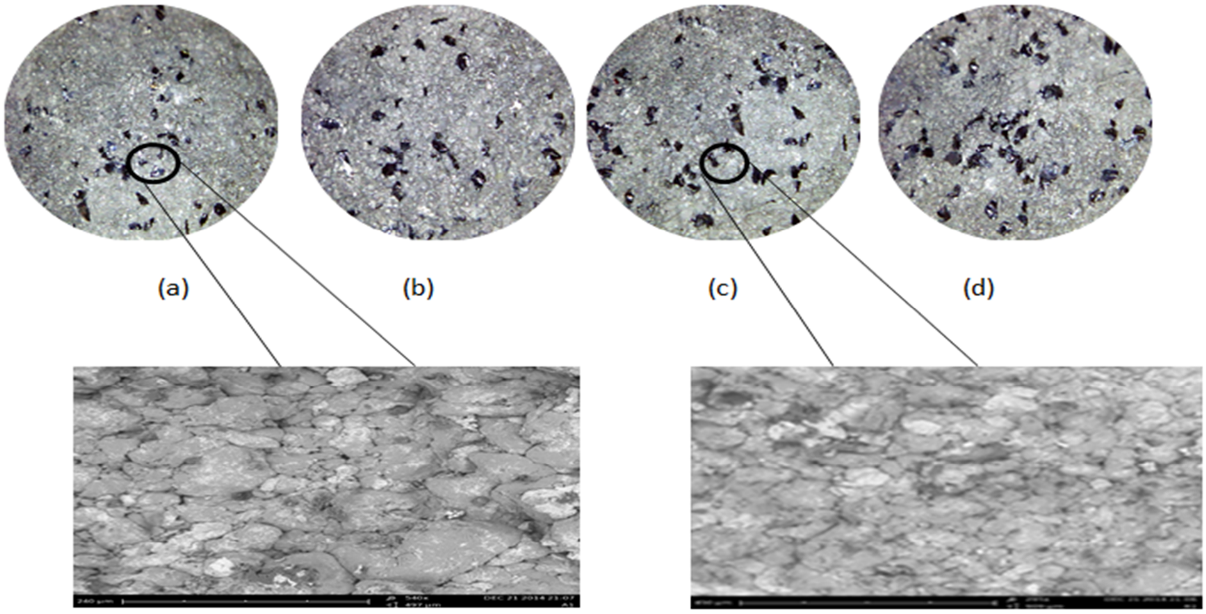

Fig. 8 Microstructure of composites:
(a) 0.5% vol. nano SiC, (b) 1.5% vol. nano SiC, (c) 3.5% vol. nano SiC and (d) 4.5% vol. nano SiC.

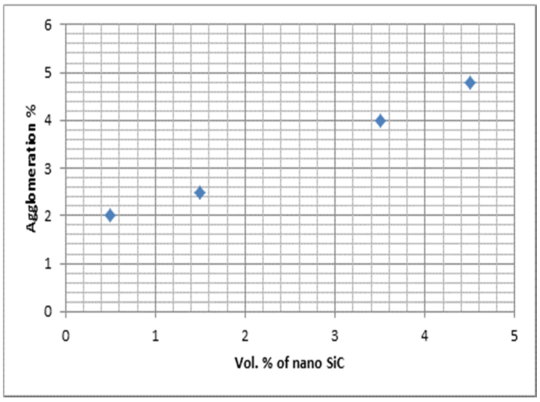

Fig. 9 SiCp agglomeration % of nano SiC

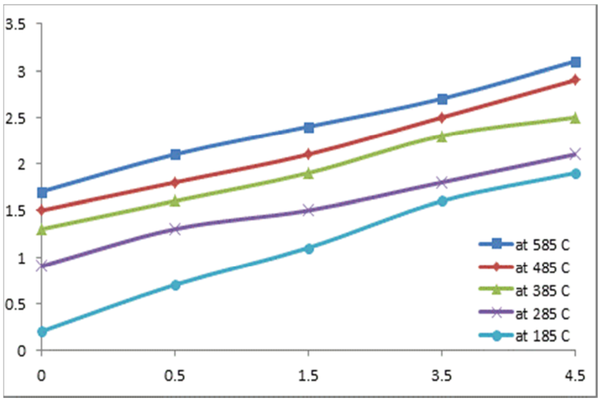

Fig. 10 Variations in the porosity related to the vol. % of nano SiC content.

The mean absolute percentage error is show in Figure 11 for various numbers of neurons in the hidden layer. The values of MAPE are given and computed at the end of the training process. Table 5 gives the MAPE errors in the prediction data.

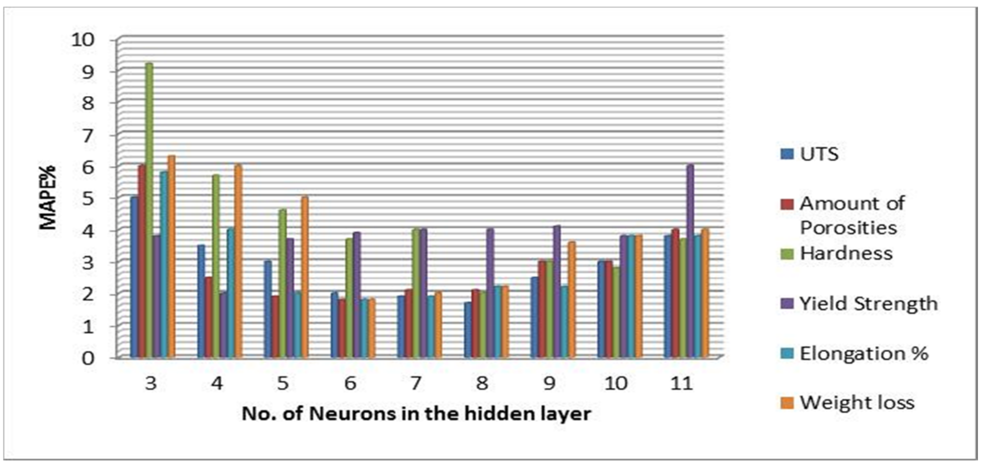

Fig. 11 The mean absolute percentage error (MAPE) for various numbers of neurons in the hidden layer

Table 5 MAPE errors in the prediction data

Properties	MAPE errors in the prediction data	No. of neurons in the hidden layer
UTS	1.7	8
Degree of porosity	1.5	6
Hardness	2	8
Yield strength	1.8	4
Elongation %	1.6	6
Weight loss	1.9	7

In the processes of prediction, weighting and training, the arbitrary starting point is altered progressively to handle numerous training examples. Therefore, the test data file for the model is verified by the cases which are independent of the training data file. Figure 12 illustrates the relationship between experimental and predicted values of hardness, elongation percentage, and weight loss of the composite. It is clearly seen from the figures that the experimental and predicted values obtained from ANNs and FEM for the wear rate are very similar. This remarkable agreement between the predicted and experimental results shows that the combination of ANN and FEM can be used in the prediction of mechanical properties. The predicted yield strength of A356 reinforced with 1 and 2.5 vol. % nano particles is shown in Figure 13.

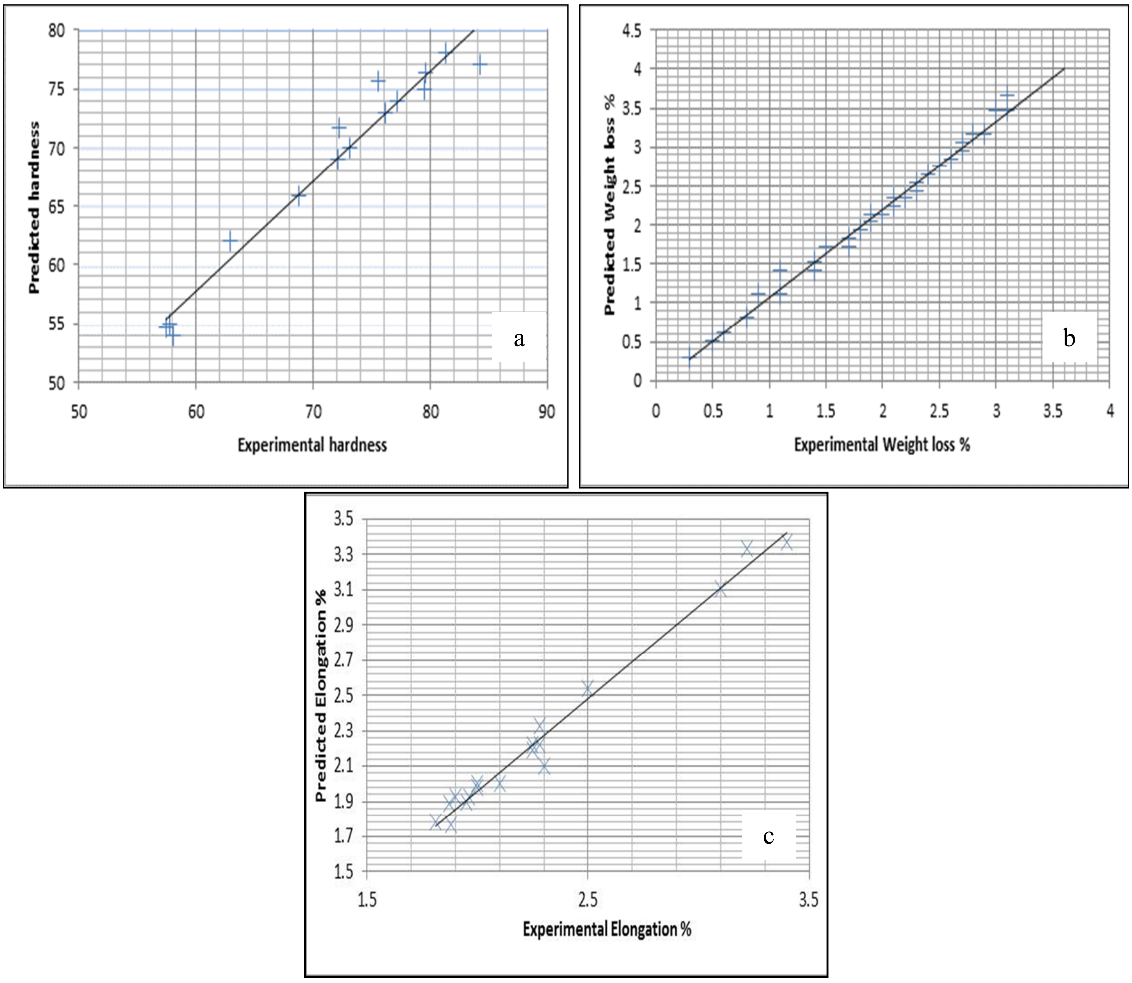

Fig. 12 The relationship between the predicted and experimental values of the composite hardness (a) weight loss % (b) and elongation % (c).

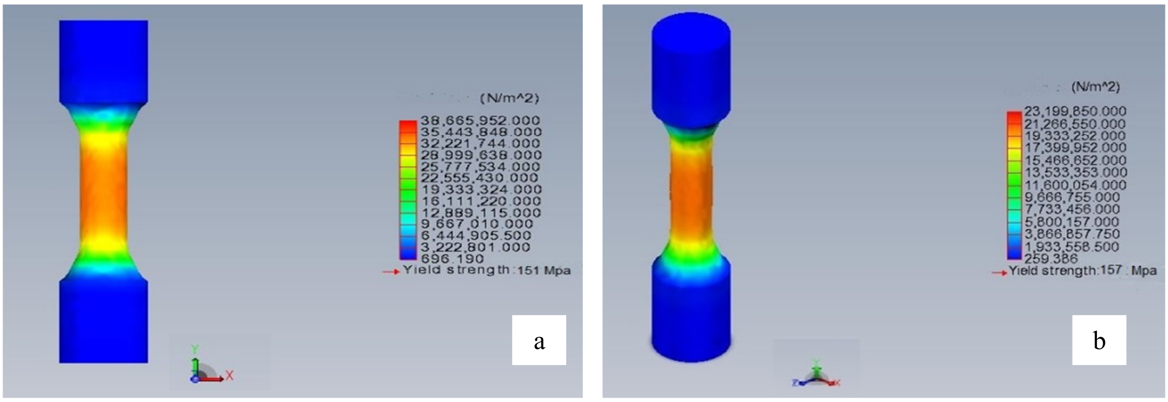

Fig. 13 Predicted yield strength of A356 reinforced with a) 1 vol. % nano SiC b) 2.5 vol. % nano SiC

5. Conclusion

The nano SiC composite has been prepared by using a powder metallurgy technique. Mechanical properties of the composites showed an increase in the wear resistance of the composite with an increased particle content. Hard nano particles protect the surface, so the wear resistance of the composite is increased with a further increase in the nanoparticle content. It was found that the addition of SiC nanoparticles to the matrix alloy increases the material hardness; this is due to the nano SiC particles acting as obstacles to the dislocation motion. The addition of nanoparticles resulted in significant improvements to the ultimate tensile strength and yield strength of the composite. Unlike experimental approaches, which are time-consuming, the combination of the finite element method and the artificial neural network method can provide approximate solutions and generalize complex relationships. Mechanical properties of the composite are related to the vol. % of SiC, temperature gradient, and cooling rate. Results obtained from the prediction model can be used as guidelines for optimizing the manufacturing processes in the conceptual design, which will reduce the time and costs related to the use of the traditional experimental methods.

NOMENCLATURE

Subscripts	
ANN	Artificial Neural Network
FEM	Finite Element Method
LMA	Levenberg Marquardt Algorithm
Vol%	Volume Fraction
Ep (w)	The error in the network pattern
JP(w)	The Jacobian matrix for vector error
AMC	Aluminium Metal Composite
MLP	Multilayer Perceptron
MAPE	Mean Absolute Percentage Error
P &I	Identity matrix
Fs	The fraction of solid
L	Latent heat
k_0	Heat coefficient (W/mK)
q	Heat generation
ρ	Density (kg/m^3)
C	Heat capacity (W/(g K)

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