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Modelling of the prediction of tensile and density properties in particle reinforced metal matrix composites by using neural networks

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Abstract

In this study, density and tensile strengths properties of Al_2O_3/SiC particle reinforced metal matrix composites (MMCs), which is produced by using stirr casting process, are predicted by designing a back-propagation neural network that uses a gradient descent learning algorithm. Firstly, to prepare a training set some results has been experimentally obtained. In the experiments, Al_2O_3/SiC powder mix has been prepared by reacting of aqueous solution of aluminium sulphate, ammonium sulphate and water containing SiC particles at 1200 °C. Ten percent vol. of this dual ceramic powder with different SiC particle size ranges was added into liquid matrix alloy (A332) during mechanical stirring between solidus and liqudus under inert condition [Altinkok N, Demir A, Ozsert İ. Composite Part A 2003;34:577–8. [1]]. Density and tensile strengths of dual ceramic reinforced aluminium matrix composites have been investigated at room temperature. In the neural networks training module, it were used different SiC (μm) particle size ranges as input and density and tensile strengths in produced MMCs. Then, neural network is trained using the data obtained in experimental process. In this paper, density and tensile strengths in produced MMCs have been estimated for different SiC (μm) particles size range by using neural network efficiently instead of time consuming experimental processes.

Keywords: Metal matrix composite; Stir casting; Density; Tensile strengths; Porous ceramic cake; Artificial neural networks

1. Introduction

Aluminium-based, particulate-reinforced metal matrix composites (MMCs) are of interest for structural applications where weight saving is of primary concern [2,3]. Ceramic particles in the ductile matrix can lead to desirable properties [4,5]. These properties include increased strength, higher elastic modulus, higher service temperature, improve wear resistance, decreased part weight, low thermal shock, high electrical and thermal conductivity, and low coefficient of thermal expansion compared to conventional metals and alloys [6,7]. There are several fabrication techniques available in manufacturing the MMC materials. According to the type of reinforcement, the fabrication techniques can vary considerably. These techniques include stir casting (called compocasting) [8,9], liquid metal infiltration [10], squeeze casting [11], and spray codeposition [12]. Compocasting involves the addition of particulate reinforcement into semi-solid metal (SSM) by means of agitation. The advantage of compocasting lies in a lower processing temperature [13], leading to a longer die life and high production cycle time [14]. Effectiveness with which mechanical stirring can incorporate and distribute the

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particles throughout the melt depends on the constituent materials, the stirrer geometry and position, the speed of stirring, and the mixture temperature. Research has been conducted in an effort to optimise the mechanical properties of MMCs [8,11,15,16]. Little of this work, however, is concerned with investigation of time required for particulate distribution. Unfortunately, in normal practice the effect of the stirring action on the flow patterns cannot be observed as they take place in a non-transparent molten metal within a furnace. As such, and because of the fact that, direct measurements of metal flow characteristics can be expensive, time consuming and dangerous, the current research focuses on methods of simulating fluid and particle flow during stirring. Very little work has been conducted to date with simulation materials for the compocasting process [17–19].

The extent of commercial use of MMCs is limited by fracture-related features. The well-known mechanisms of fracture are the progressive damage, which originates from particle fracture and interfacial decohesion leading to void formation in the matrix, the growth of pre-existing voids found largely in particle clusters where the reinforcement has not been fully wetted by the matrix, and the damage introduced during prior thermo mechanical treatment of the materials [4,5]. The fracture resistance of particle reinforced MMCs has been the subject of active research for many years. Generally, It is recognized that fracture-related features of MMCs can be improved by both intrinsic and extrinsic mechanisms [20,21]. Interior mechanisms improve fracture features with increasing the inherent microstructural resistance to crack growth through control of intrinsic characteristics such as particle size, reinforcement amount, and the microstructure of matrix. On the other hand, exterior mechanisms, improve fracture features by providing alternative crack propagation routes or reducing the driving force for crack growth through various processes that shield the crack tip from the applied stress. These processes consist of crack defection, crack bridging and crack trapping [22,23].

In this study, the results have shown that density properties and tensile strengths in particle reinforced aluminium matrix composites have been predicted with an acceptable accuracy by neural network. Recently, an attempt has been made to investigate the possibility of using neural networks in prediction of the results of the time consuming experimental processes, which have not been done, using some previously done experimental results in neural network training [24–26]. A good example has been reported to design catalysts for ammoxidation of propylene [27]. Further research indicates that this method is easy to understand and could be used for prediction of experimental studies of different chemical reactions by changing the structural organization of the chemical mixes [28].

2. Experimental

In this section, experimental processes have been presented with all details. Artificial neural networks have the ability of learning non-linear processes due to the learning ability by using previously obtained data. So, some experimental data has been prepared to train neural network from obtained experimental data in this section.

2.1. Tensile test and microstructure analysis

Tensile test of the cast composites carried out by a DARTEC 94052 RK type testing machine at room temperature with 1 m/s speed under. According to Haunsfield Testing BS 564 standard was prepared test specimens. Optical microscope (Olympus BH2-UMA) was used to examine particle distribution and SEM (JEOL 5600), and with attached EDS analysis at low (5 kV) voltage were used to investigate polish surfaces. The density measurement was performed by a weight loss method using an electron balance. The theoretical density was calculated as $1 - \rho_m/\rho_{th}$ where ρ_m and ρ_{th} are the measured.

Magnesium and silicon in liquid aluminium increased the wettability of the matrix and assisted to the particle incorporation. An optical microstructure of the stir cast composite is shown in Figs. 1 and 2. This figure shows that large SiC particles with small Al_2O_3 particles reinforced MMC was successfully produced. As shown in Fig. 1, (a) fine alumina particles >5 μm are uniformly distributed inter-particle spacing of coarse SiC particles. The microstructure of alloy is dependent on the cooling rate of casting. This effect becomes important in the case of composite because Al_2O_3/SiC particle distribution is affected by growing aluminium are pushed by the leading edges of growing aluminium dendrites and then trapped by converging dendrites arms in the intercellular regions. The cooling rate, and therefore influences the distribution of SiC particles in the casting. SEM and optical views of the polish surfaces with their EDS analyses of the matrix alloy are shown in Fig. 1(a) and (b). Oxygen and carbon peak from the EDS analysis in Fig. 1(b) confirms that Al_2O_3 and SiC particles are present within the composites, whereas in Fig. 1(a), these elements do not exist showing Al–Si–Mg matrix alloy.

The strength of the composites depends somewhat on the uniformity of Al_2O_3/SiC particles distribution. Uniform distribution of Al_2O_3/SiC particles is in a high strength. As shown Table 1, tensile strengths of Al_2O_3/SiC particle reinforced A332 matrix composites have been decreased because of increasing particle size. SEM micrographs of the fracture surfaces of A332 and MMC tensile bars have been revealed in Fig. 2(a) and (b). In Fig. 2(a), because of the strong particle/matrix alloy bond resistance, the dendrite arms have

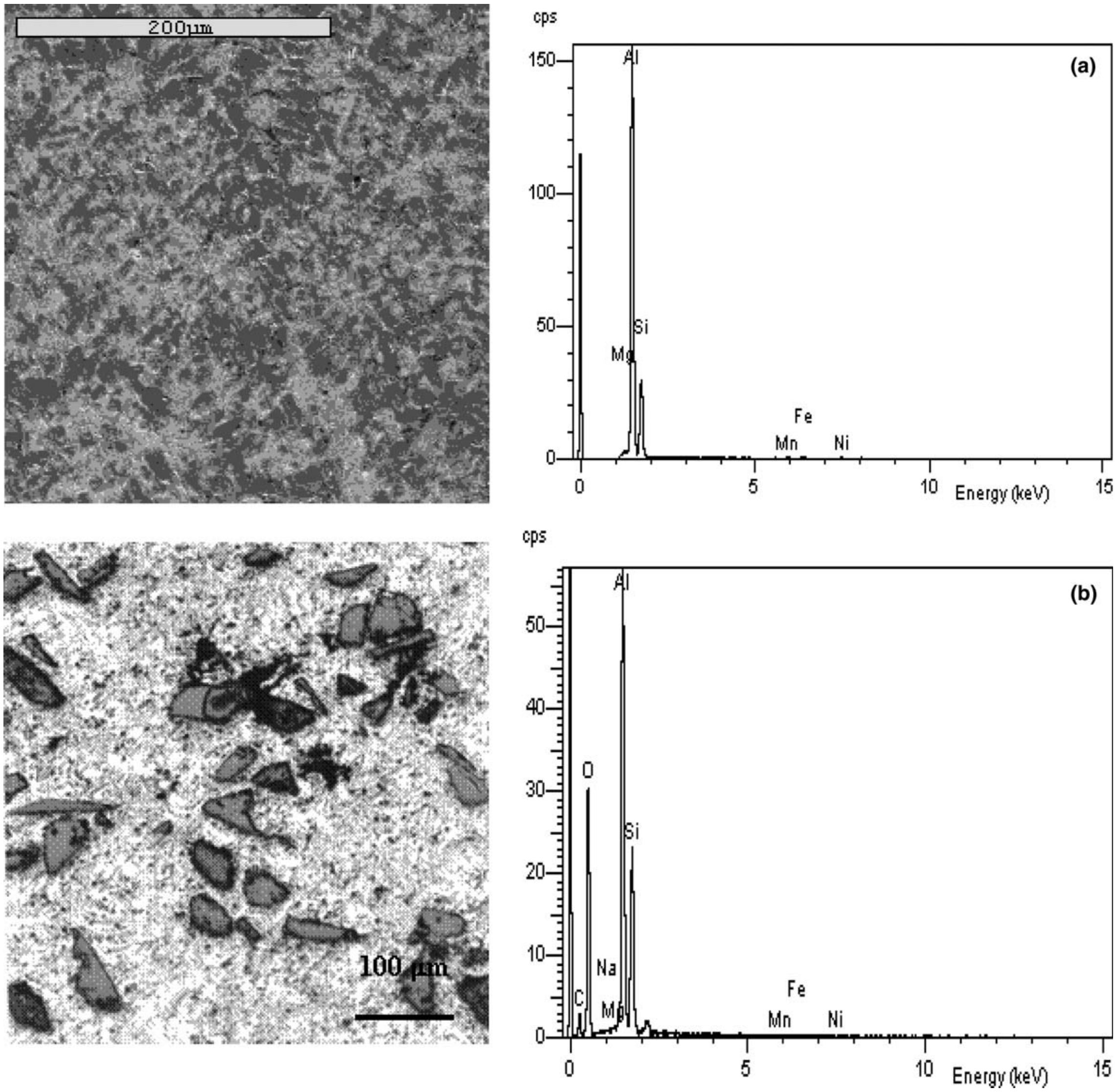

Fig. 1. (a) A332 matrix alloy SEM micrograph. (b) SiC with Al_2O_3 reinforced MMC Optical micrograph and their EDS analysis.

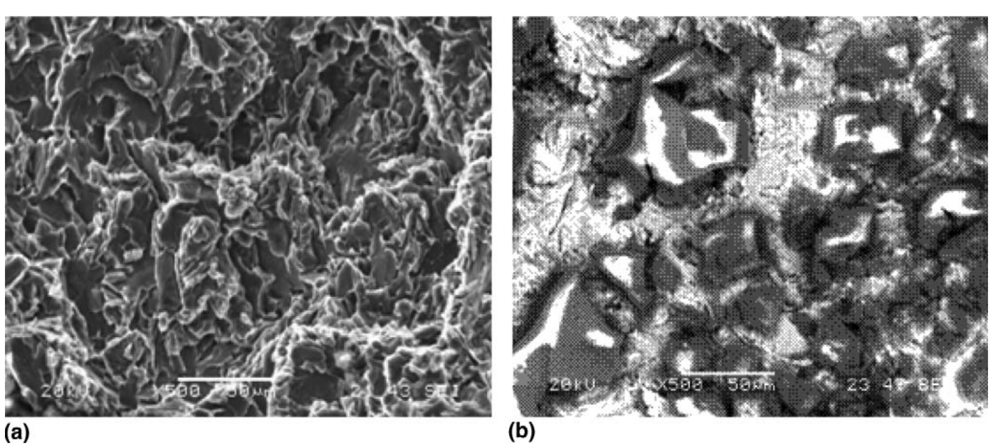

Fig. 2. (a) Fracture surface of A332 matrix alloy. (b) SiC with Al_2O_3 reinforced MMC and SEM micrograph their EDS analysis.

become smaller and thinner. It is clearly seen in Fig. 2(b) that reinforcement of particles into liquid alimunium matrix alloy produced by Stirr casting method have been implemented uniformly distributed. This property of MMCs has increased the tensile strength due to uniformly distribution and the decreasing particle size.

Table 1
The experimental results of MMCs used in neural network training set

Samples	Inputs of network	Output #1	Output #2
	Particle size (μm)	Experimental tensile strengths (MPa)	Experimental density (g/cm^3)
S(1)	2	287.1	2.6943
S(2)	4	275.4	2.6998
S(3)	8	268.3	2.7001
S(4)	10	254.7	2.7018
S(5)	16	251.3	2.7034
S(6)	20	248.6	2.7075
S(7)	27	245.1	2.7084
S(8)	38	241.8	2.7096
S(9)	45	239.2	2.7147
S(10)	49	236.2	2.7203
S(11)	53	233.9	2.7259
S(12)	60	229.2	2.7268
S(13)	67	225.9	2.7287
S(14)	75	221.8	2.7301
S(15)	87	219.5	2.7347

Gui et al. [29] has investigated the tensile strength, and density properties of the MMCs, which has been produced by the way same method. In their study, the cavities among the aggregated SiC particles tend to decrease the composite densities. So, the density of composites is a basic criterion with which to evaluate their quality. Table 1 gives the values of density of the composites after experiment. Similar results have been found in this study. It is found that employing the experiments following liquid stirring has caused an evident increase in density of two composites, resulting in a significant improvement in quality of composites.

3. Neural network approach

An artificial neural network is a parallel-distributed information processing system. It stores the samples with distributed coding, thus forming a trainable nonlinear system. The main idea of neural network approach resembles the human brain functioning. Given the inputs and desired outputs, it is also self-adaptive to the environment so as to respond different inputs rationally [30,31]. The aim of this paper is to investigate the prediction of density properties and tensile strengths in particle reinforced aluminium matrix composites by training a neural network.

The neuron shown in Fig. 3 can be classified into three types based on their inputs and outputs: input, output, hidden neurons. Input neurons are the ones that

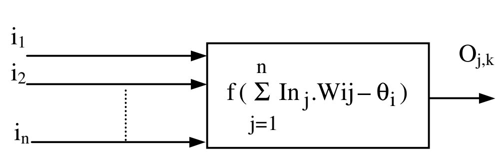

Fig. 3. Neuron structure.

receive input from the environment, such as SiC (μm) particle. Output neurons are those that send the signals out of the system, and neurons, which have inputs and outputs within the system, are called hidden neurons: where In_j is the input signal from the jth neuron. W_{ij} is the weight value on the interconnection from neuron j to neuron i. θ_i is the threshold for the ith neuron. O_i is the output signal of the ith neuron. $f(\ )$ is the activation function.

The purpose of activation function in the neuron is to confine the neuron's output to a pre-specified range. Sigmoid activation function, which is a continuous, nonnonlinear, monotonic non-decreasing and S-shaped, has been used in this study. The sigmoid activation function is given as follows:

$$f(x) = \frac{1}{1 + e^{-x}}. \quad (1)$$

In this study, the back propagation, which is a widely used algorithm, is used in training. It can map non-linear processes. It is a feed forward network with one or more hidden layers. The elementary architecture of the back propagation network has three layers. There are no constraints about the number of hidden layers. Back propagation is a systematic method for training multiplayer artificial neural networks. It has a strong mathematical foundation based on gradient descent learning. In Fig. 4, a sample multi-layer feed forward net structure, which has one hidden layer, is given, and all parameters are given according to this figure below [32]. This figure has also been arranged according to the neural network implementation as a prediction in this study.

Multi-layer Perceptron (MLP) trained using the back propagation algorithm has been found very successful in this study. Learning in an MLP model involves using an iterative gradient descent algorithm to minimize the

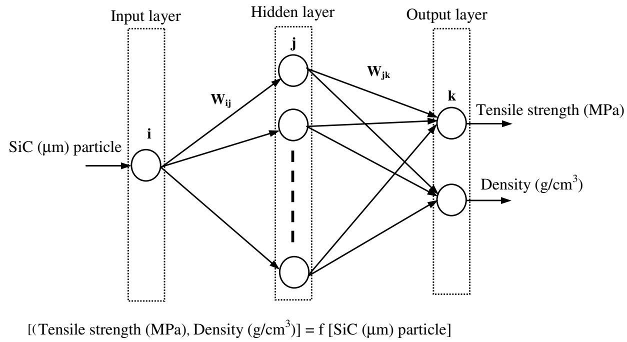

Fig. 4. The structure of designed neural network.

mean square error between the actual outputs of the network and the desired outputs in response to given inputs. Training in an MLP network is performed by forward and backward operation, the network produces its actual outputs for a certain input pattern using the current connection weights. Subsequently, the backward operation is carried out to alter the weights to decrease the error between the actual and desired outputs. The alteration of weights is affected by two parameters, namely learning rate and momentum coefficient. The learning rate defines the range of the changes in the connection weights. The momentum coefficient is introduced to improve the learning process and it works by adding a term to the weight adjustment that is proportional to the previous weight change [33].

The error is computed using the Eqs. (2) and (3) known as average squared error [30]. Here, N denotes the total number of samples in training set, and the set C includes all the neurons in the output layer of the network.

$$e_k(n) = d_k(n) - y_k(n), \tag{2}$$

$$\varepsilon_{\mathrm{av}} = \frac{1}{2N}\sum_{n=1}^{N}\cdot\sum_{k\in C} e_k^2(n). \tag{3}$$

In training of BP neural network, 15 input and output vector sets are generated from the experiments. Ten of these are used as learning set, and others are used in test. Due to the characteristic of sigmoid activation function, the training set is scaled between 0 and 1. Learning rate and the momentum rate are experimentally chosen as 0.2 and 0.9, respectively. Eight neurons are used in hidden layer.

The training process has been completed approximately in 200.000 iterations. When the training is completed, a neural network is designed using the obtained weights as seen in Fig. 4.

4. Results and discussion

In this paper, density and tensile strengths properties of Al_2O_3/SiC particle reinforced MMCs were predicted by designing a back-propagation neural network that uses a gradient descent-learning algorithm. The neural network results were obtained with a good agreement with experimental results. Firstly, the tensile strength, and density properties of the composite were found a produced by stir casting. The hardness and the tensile strength of the composites are increasing with decreasing particle size. In addition, tensile strength values increased of the composites. This was result from bonding between Al_2O_3/SiC and the matrix. At the end of these experimental processes, the neural network training module was used for prediction of tensile strength and density behaviour and also density properties of MMCs produced in different SiC particles size. The neural network results confirmed the feasibility of this approach and showed a good agreement with experimental results produced by MMCs. These results were confirmed possibility of using the neural network model for the prediction of tensile strength and density properties and the result.

The neural network software has been developed using Delphi Programming language. The obtained prediction results for testing patterns have been given in Figs. 5 and 6. The results obtained in training set have the less error then one in test sets. Because training set is directly used in teaching neural network the non-linear problem. So, neural network has given the results with an accuracy error for learning (training) set. On the other hand, the prediction results of testing patterns are actually for the system success because of the fact that they are not used during the training period. To say about the results about testing data, neural network predictions are similar with experimental data as seen in Figs. 5 and 6. The error at the end of the learning is 0.000472 for training set.

At the end of the neural network implementation, the result for tensile strength is nearly with the experimental results. Similarly, the results for density are found satisfactory. However, some points on the curve in Fig. 6 have value with much error according to other points

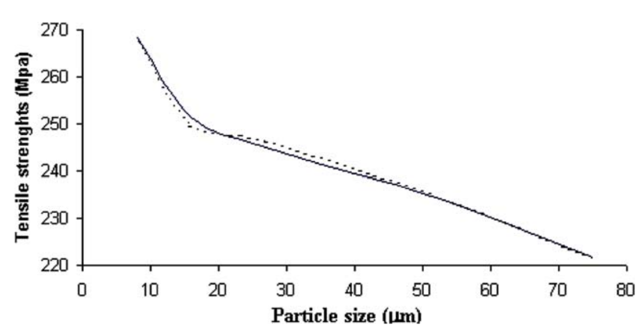

Fig. 5. The curves of experimental and neural network results of tensile strength according to particle size.

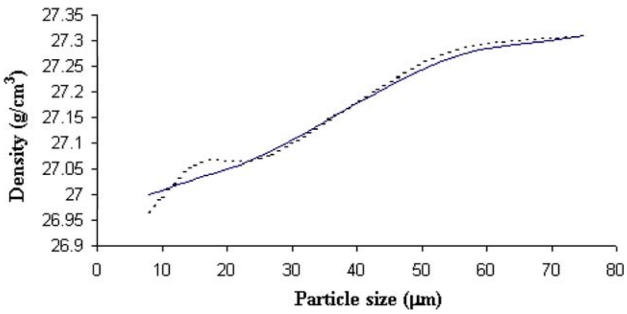

Fig. 6. The curves of experimental and neural network results of density according to particle size.

on the curve. But, the data structure of the density which is given in Table 1 is more difficult from the view point of having a relationship between any given particle size and density because of the floating points on the numbers. On the other hand, all values have been arranged according to used sigmoid activation function. This also improves the sensitivity of neural network to the numbers in the training set.

In Fig. 5, the curve of the experimental result and neural network prediction results of tensile strength according to the given particle size has been presented as a graphic. Fig. 6 reveals the effect of Al_2O_3/SiC particle size on tensile strength obtained experimentally by using neural network. Initially because of obtainability of peaks in the preliminary phase, percentage improvement in tensile strength value is a little high, however, as these peaks obtain machined the percentage improvement in tensile strength value decreases slowly. In the graphics in the Figs. 5 and 6, the dotted line refers to the neural network results and the straight line refers to the experimental results.

Fig. 6 reveals that density properties value decreases with decreasing in particle size. This is because of the fact that, the porosity values have been increased due to the fact that increasing particle surface areas where they contact with air, and under these circumstances density values have been decreased. Furthermore, because of the porous the gathered Al_2O_3/SiC particles and in the matrix, the composites density has been decreased. Therefore, it can be said that a basic criterion with which to evaluate their quality is the density of composites.

5. Conclusion

In this paper, a neural network is designed to predict density properties and tensile strengths in particle reinforced aluminium matrix composites according to given SiC particle size (μm). The generalization ability of the neural network is the basic consideration in this paper. It was observed that neural network found successful in prediction of experimental results instead of time-consuming studies. For future study, Elman and Jordan type neural networks, radial function and quick back-propagation, etc., can be used in these kinds of predictions.

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