Use of artificial neural network for prediction of physical properties and tensile strengths in particle reinforced alüminum matrix composites

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Aluminum-based, particulate-reinforced Metal Matrix Composites (MMCs) were of interest for structural applications where weight saving was of primary concern [1, 2]. Ceramic particles in the ductile matrix lead to desirable properties [3, 4]. These properties include increased strength, higher elastic modulus, higher service temperature, improved 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 [5, 6]. There were several fabrication techniques available in manufacturing the MMC materials. According to the type of reinforcement, the fabrication techniques obtained vary considerably. These techniques included stir casting (compocasting) [7, 8], liquid metal infiltration [9], squeeze casting [10], and spray codeposition [11]. Compocasting involves the addition of particulate reinforcement into semisolid metal by means of agitation. The advantage of compocasting lies in a lower processing temperature [12], leading to a longer die life and high production cycle time [13]. Little of this work, however, was concerned with investigation of time required for particulate distribution. Unfortunately, in normal practice the effect of the stirring action on the flow patterns was observed as they took place in a non-transparent molten metal within a furnace. As such, and because of the fact that, direct measurements of metal flow characteristics was made expensive, time consuming and dangerous, the current research focuses on methods of simulating fluid and particle flow during stirring. Very little work had been conducted to date with simulation materials for the compocasting process [14–16].

The fracture resistance of particle reinforced MMCs were made the subject of active research for many years. Generally, it was recognized that fracture-related features of MMCs were improved by both intrinsic and extrinsic mechanisms [17, 18]. Interior mechanisms improved 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, improved 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 consisted of crack defection, crack bridging and crack trapping [19, 20].

Experimental processes were presented with all details. Artificial neural networks were the ability of learning non-linear processes due to the learning ability by using previously obtained data. So, some experimental data was prepared to train neural network from obtained experimental data.

Microstructure of the stir cast composite showed that large SiC particles with small Al_2O_3 particles reinforced MMC was successfully produced. Fine alumina particles $>5\ \mu$m are uniformly distributed inter-particle spacing of coarse SiC particles. The microstructure of the alloy is dependent on the cooling rate of casting. This effect becomes important in the case of the composite because the Al_2O_3/SiC particle distribution is affected by the growing aluminum, in that the leading edges of the growing aluminum dendrites push the Al_2O_3/SiC particles which are then trapped by the converging dendrites arms in the intercellular regions. The cooling rate, therefore, influences the distribution of SiC particles in the casting. EDS analyses of the matrix alloy showed oxygen and carbon peak from the EDS analysis confirmed that alumina and SiC particles are present within the composites, whereas these elements did not exist showing Al-Si-Mg matrix alloy.

Gui *et al.* [21] investigated the tensile strength, density and porosity properties of the MMCs, which was produced by the 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 I gives the values of density and porosity of the composites after experiment. Similar results were found in this study. It was found that employing the experiments following liquid stirring caused an evident increase in density of two composites, resulting in a significant improvement in quality of composites.

The aim of this paper was to investigate the prediction of physical properties and tensile strengths in particle

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TABLE I The neural network training and test set*

	Inputs of networks	Outputs of neural network		
		Output # 1	Output # 2	Output # 3
		Experimental values		
Samples	Particle size (μm)	Tensile strengths (MPa)	Density (g/cm^3)	Porosity (%)
S(1)	2	287.1	2.6943	3.33
S(2)	4	275.4	2.6998	3.16
S(3)	8	268.3	2.7001	3.14
S(4)	10	254.7	2.7018	3.03
S(5)	16	251.3	2.7034	3.03
S(6)	20	248.6	2.7075	2.83
S(7)	27	245.1	2.7084	2.85
S(8)	38	241.8	2.7096	2.76
S(9)	45	239.2	2.7147	2.56
S(10)	49	236.2	2.7203	2.42
S(11)	53	233.9	2.7259	2.22
S(12)	60	229.2	2.7268	2.19
S(13)	67	225.9	2.7287	2.12
S(14)	75	221.8	2.7301	2.07
S(15)	87	219.5	2.7347	1.91

*Ten of them were used in the training set. Others were used in test set.

reinforced aluminum matrix composites by training a neural network. Back propagation algorithm was used in the training with one hidden layer. Back propagation was a systematic method for training multi-player artificial neural networks. It was a strong mathematical foundation based on gradient descent learning. The neural network software was developed using Delphi Programming language. A sample multi-layer feed forward net structure, which has one hidden layer, is given, and all parameters are given according to this (Fig. 1 [22]).

Table I shows that with decreasing in particle size, density properties value decreases. This is due to the fact that, the porosity values have increased because of increasing particle surface areas when they are in contact with air, and under these circumstances the density values have decreased. In addition, the composites' density has decreased because of the porous nature gathered by Al_2O_3/SiC particles in the matrix. So, the density of composites is a basic criterion with which to evaluate their quality. Small particles in the composites caused crackling under mechanical forces. This situation on the composites including small particles showed higher tensile strength and hardness. Due to the fact that dislocation movement was inhibited and the shape changing becomes difficult, particle size decreased. This feature increased the tensile strength and hardness resistance values. In the microstructure of the MMC produced, the Al_2O_3/SiC particle distributions were homogeneous in the matrix. The fracture surfaces of the MMCs showed friable fracture characteristics, on the fracture surfaces of the composites, broken and cracked Al_2O_3/SiC particles were observed and the cracks were initiated in the friable eutectic silicon phase.

A neural network that uses gradient descent error learning was designed and used in the prediction. The designed neural network was 1 input and 3 outputs. In training of BP neural network, 15 input and output vector sets are generated from the experiments. Ten of these are used as learning sets, 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, experimentally, as 0.3 and 0.8, respectively. The number of neurons in the hidden layer was generally selected experimentally, and 12 neurons in the hidden layer were found successful in training process, and decided experimentally. The training process has been completed approximately in 520.000 iterations. When the training is completed, a neural network is designed using the obtained weights as seen in Fig. 1 and given in Table II as values. The error of the system was computed by using MSE (Mean Square Error) given in Equations (1) and (2), and error at the end of learning process was 0.0000182. Here, N denotes the total number of samples in training set, and the set C includes all the neurons

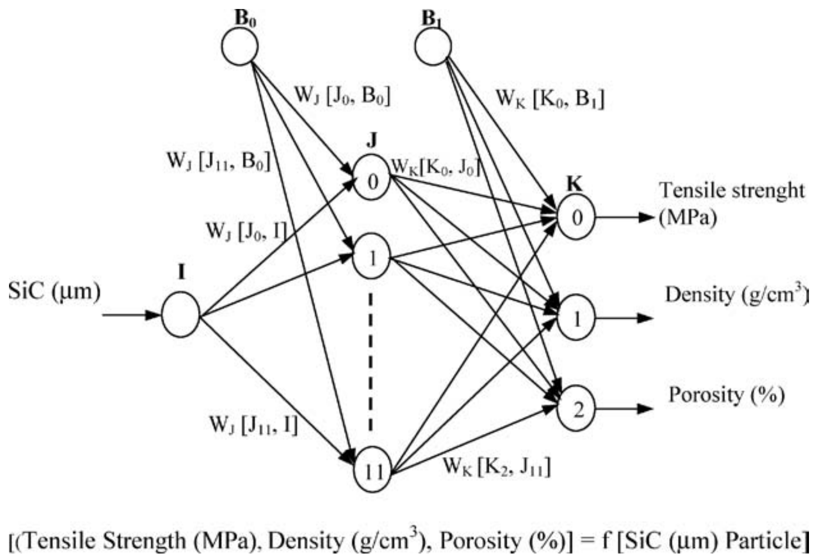

Figure 1 The structure of designed neural network.

TABLE II Obtained weights at the end of training process

$W_J[J_0, I] = 41.191546119$	$W_K[K_0, B_1] = 3.595394631$	$W_K[K_1, J_{10}] = -1.179873373$
$W_J[J_0, B_0] = -20.25175778$	$W_K[K_0, J_0] = -1.315998097$	$W_K[K_1, J_{11}] = -1.482848066$
$W_J[J_1, I] = -28.960835271$	$W_K[K_0, J_1] = -3.716089238$	$W_K[K_2, B_1] = 6.716179013$
$W_J[J_1, B_0] = 13.819779391$	$W_K[K_0, J_2] = -0.766354169$	$W_K[K_2, J_0] = -4.350504363$
$W_J[J_2, I] = -3.676852876$	$W_K[K_0, J_3] = -5.809247370$	$W_K[K_2, J_1] = -9.271330282$
$W_J[J_2, B_0] = -2.311909835$	$W_K[K_0, J_4] = 2.280197470$	$W_K[K_2, J_2] = -0.642358420$
$W_J[J_3, I] = 15.981138421$	$W_K[K_0, J_5] = 1.000575782$	$W_K[K_2, J_3] = -10.134725479$
$W_J[J_3, B_0] = -6.879953219$	$W_K[K_0, J_6] = 1.129937214$	$W_K[K_2, J_4] = 6.502112074$
$W_J[J_4, I] = 2.837895112$	$W_K[K_0, J_7] = -6.538942956$	$W_K[K_2, J_5] = 1.011886902$
$W_J[J_4, B_0] = 2.437500377$	$W_K[K_0, J_8] = 0.806499968$	$W_K[K_2, J_6] = 0.658500810$
$W_J[J_5, I] = -0.547140353$	$W_K[K_0, J_9] = 0.672846289$	$W_K[K_2, J_7] = -7.663237777$
$W_J[J_5, B_0] = -1.372896373$	$W_K[K_0, J_{10}] = 15.270444967$	$W_K[K_2, J_8] = 0.899646829$
$W_J[J_6, I] = -1.731442374$	$W_K[K_0, J_{11}] = 0.0289922607$	$W_K[K_2, J_9] = 0.553607250$
$W_J[J_6, B_0] = -1.100640484$	$W_K[K_1, B_1] = -1.893904428$	$W_K[K_2, J_{10}] = 9.320139684$
$W_J[J_7, I] = -16.399013021$	$W_K[K_1, J_0] = 0.599911896$	$W_K[K_2, J_{11}] = 0.440289365$
$W_J[J_7, B_0] = 4.712174020$	$W_K[K_1, J_1] = 1.308300527$	
$W_J[J_8, I] = -0.809892501$	$W_K[K_1, J_2] = -0.835698109$	
$W_J[J_8, B_0] = -1.633792400$	$W_K[K_1, J_3] = 1.4855900542$	
$W_J[J_9, I] = -2.047123965$	$W_K[K_1, J_4] = -0.466955518$	
$W_J[J_9, B_0] = -1.567927474$	$W_K[K_1, J_5] = -1.012674167$	
$W_J[J_{10}, I] = -39.119896334$	$W_K[K_1, J_6] = 0.633805999$	
$W_J[J_{10}, B_0] = 9.731174280$	$W_K[K_1, J_7] = 1.106677362$	
$W_J[J_{11}, I] = 0.491177643$	$W_K[K_1, J_8] = -0.803157638$	
$W_J[J_{11}, B_0] = -1.990067054$	$W_K[K_1, J_9] = 0.891615827$	

Note. The representation of all abbreviations used in this table are given in Fig. 1.

TABLE III Obtained results from the neural network for training set

Samples	Particle size (μm) input	Experimental tensile strengths (MPa)	Neural network outputs	Experimental density (g/cm^3)	Neural network outputs	Experimental porosity (%)	Neural network outputs
S(1)	2	287,1	287.43	2,6943	2.6951	3,33	3.30
S(2)	4	275,4	274.24	2,6998	2.6987	3,16	3.18
S(4)	10	254,7	254.99	2,7018	2.7025	3,03	3.01
S(6)	20	248,6	248.41	2,7075	2.7073	2,83	2.83
S(8)	38	241,8	242.18	2,7096	2.7092	2,76	2.76
S(9)	45	239,2	238.81	2,7147	2.7148	2,56	2.57
S(10)	49	236,2	236.02	2,7203	2.7196	2,42	2.42
S(12)	60	229,2	229.60	2,7268	2.7263	2,19	2.20
S(13)	67	225,9	225.98	2,7287	2.7292	2,12	2.10
S(15)	87	219,5	219.32	2,7347	2.7345	1,91	1.91

TABLE IV Obtained results from neural network for testing patterns

Samples	Particle size (μm) input	Experimental tensile strengths (MPa)	Neural network outputs	Experimental density (g/cm^3)	Neural network outputs	Experimental porosity (%)	Neural network outputs
S(3)	8	268,3	258.71	2,7001	2.7018	3,14	3.04
S(5)	16	251,3	250.36	2,7034	2.7047	3,03	2.91
S(7)	27	245,1	244.55	2,7084	2.7114	2,85	2.71
S(11)	53	233,9	233.51	2,7259	2.7229	2,22	2.31
S(14)	75	221,8	222.60	2,7301	2.7321	2,07	2.01

in the output layer of the network [23].

$$e_k(n) = d_k(n) - y_k(n) \tag{1}$$

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

In Tables III and IV, the experimental and neural network prediction results of tensile strength, density and porosity, according to particle size have been given for training and test sets. The training is more difficult due to the structure of the data in density values because of floating points in values.

The neural network prediction results showed a good agreement with experimental results. It is clearly seen in Tables III and IV that the neural network predicts physical properties and tensile strengths in particle reinforced aluminum matrix composites according to given SiC particle size (μm), succesfully. The basic consideration of this paper is to predict the result of the experiments, which has not been done, by using some of realized experimental values instead of time consuming experiments. Considerable savings in terms of cost and time were obtained from using neural network model, neural network results revealed a good accord with experimental data, and neural network supplied further beneficial data from comparatively small experimental databases. Very good performance of the trained neural network was achieved.

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