Available online at www.sciencedirect.com
ScienceDirect
Materials and Design 28 (2007) 616–627
Materials & Design
www.elsevier.com/locate/matdes

Neural network based prediction of mechanical properties of particulate reinforced metal matrix composites using various training algorithms

Rasit Koker [a,*], Necat Altinkok [b], Adem Demir [b]

[a] Department of Computer Engineering, Engineering Faculty, Sakarya University, Esentepe 54187 Sakarya, Turkey
[b] Department of Metal Education, Technical Education Faculty, Sakarya University, Esentepe 54187 Sakarya, Turkey

Received 15 March 2005; accepted 22 July 2005
Available online 28 September 2005

Abstract

Recently, artificial neural networks are used as an interdisciplinary tool in many applications. There are various training algorithms used in neural network applications. In this study, it is aimed to investigate the effect of various training algorithms on learning performance of the neural networks on the prediction of bending strength and hardness behaviour of particulate reinforced Al–Si–Mg metal matrix composites (MMCs). Al_2O_3/SiC particulates reinforced MMC was produced by using stir casting process. Al_2O_3/SiC powder mix obtained from Al_2O_3/SiC ceramic cake, which was produced firing of aluminium sulphate aqueous solution and SiC mix before stir casting. In the experimental processes, during fabrication, stirring was applied to create a vortex for addition reinforcing particles and the production of aluminium alloy metal-matrix composites. 10 vol.% of dual ceramic powder with different SiC particle size range mix was inserted in liquid aluminium by using stir casting under Ar pressure to obtain dual particulates reinforced MMCs. This mixing was achieved successfully; microstructure, bending strength and hardness properties of the composites were tested. Bending strength and hardness behaviour were predicted with four different training algorithms using a back-propagation neural network. The training and test sets of the neural network were initially prepared using experimental results that were obtained and recorded in a file on a computer. Test results revealed that bending strength and hardness resistance of the composites increased with decrease in ductility, with decrease size of the reinforcing SiC particulates in the aluminium alloy metal matrix. In the training and test modules of the neural network, different SiC particles size (μm) range was used as input and bending strength and hardness behaviour were used as output in the produced MMCs. After the preparation of the training set, the neural network was trained using four different training algorithms. For each algorithm, the results were analyzed. The test set was used to check the system accuracy for each training algorithm at the end of learning. In conclusion, Levenberg–Marquardt (LM) learning algorithm gave the best prediction for bending and harness behaviours of aluminium metal matrix composites.

Keywords: Metal matrix composites production; Stir casting; Mechanical properties; Artificial neural networks; Training algorithms

1. Introduction

Metal matrix composites (MMCs) have received considerable attention because of their superior properties as compared to those of most conventional materials. MMCs exhibit a high specific strength, stiffness and wear resistance, in addition to a service temperature capability, that is much higher than that of other materials or composites. They are also excellent thermal conductors. Therefore, MMCs are now used in, or being considered for use in, a variety of applications, such as connecting rods, automotive drive shafts, cylinder liners and brake rotors [1]. They typically include ceramic particles to improve their mechanical properties. The high strength to weight ratio of MMC enables it to be applied extensively in the aerospace industry [2]. Concurrent with the rapid strides in developing economically viable and attractive processing

* Corresponding author. Tel.: +90 264 346 03 53; fax: +90 264 346 03 51.
E-mail addresses: rkoker@sakarya.edu.tr (R. Koker), altinkok@sakarya.edu.tr (N. Altinkok), ademir@sakarya.edu.tr (A. Demir).

0261-3069/$ - see front matter
doi:10.1016/j.matdes.2005.07.021

Nomenclature

MMCs	metal matrix composites
Al_2O_3/SiC	alumina/silicon carbide
A332	aluminium code
µm	micron meter
ρ_m	matrix density
ρ_{th}	theoretical density
EDS	energy dispersive spectroscopy
SEM	scanning electron microscope
MPa	mega pascal
HB	hardness Brinell
LM	Levenberg–Marquardt
QN	quasi-Newton
RBP	resilient back propagation
VLRBP	variable learning rate back propagation
i, j, k	different neurons in the network (in different layers)
In_j	The input signal from the jth neuron
W_{ij}	the weight value on the interconnection from neuron j to neuron i
θ_i	the threshold for the ith neuron
O_i	The output signal of the ith neuron
$f(\ )$	the activation function
MLP	multilayer perceptron
B	Bias
$F(s)$	a non-linear function
t	the threshold level given by user
n	n_{th} training pattern(example) presented to the network
MSE	mean squared error
$w_{ji}(n)$	the synaptic weight connecting the output of neuron i to the input of neuron j at iteration n
w_{nj}	the weight associated with the line from element n to element j
I	input vector to unit n
η	the learning rate parameter
α	the momentum constant
$F(I)$	the sigmoid function
$F'(I)$	the derivative of the sigmoid function
N	the total number of samples in training set
C	the set including all the neurons in the output layer of the network
$e_k(n)$	the error signal at the output of neuron k for iteration n
$d_k(n)$	the desired response for neuron k
$y_k(n)$	the function signal appearing at the output neuron k at iteration n
$\varepsilon(n)$	the instantaneous sum of error squares at iteration n
$\varepsilon_{av}(n)$	the average squared error

routes for these heterogeneous materials [3]. In particular, particle-reinforced metal matrix composites are attractive highly versatile engineering materials having attractive combinations of density, strength, stiffness, reliability and structural efficiency. Furthermore, these materials can be processed and finished by conventional metal fabrication techniques.

Particle reinforced aluminum composites are being recognized as an important class of engineering material that is making significant progress. The attractiveness in preferring and choosing a discontinuously reinforced MMC, for many applications stems from an improvement in specific modulus, that is, the density compensated increase in elastic modulus [4]. In addition, which include low density, high specific stiffness, and controlled coefficient of thermal expansion, superior dimensional stability and increased tensile strength [5].

Recently, artificial neural networks have taken a great deal of attention as a prediction and modeling tool in many research areas; such as electronics, automotive, robotics, medical diagnosis, chemistry, etc. Artificial neural networks can be used in such applications as prediction, classification, recognition, and modeling. It can be defined as massively parallel-distributed processors, which have a natural tendency to store experiential knowledge and making it available to use. Its working principle can be resembled the human brain due to its functions in two ways: (i) the neural network through a learning process acquires knowledge and (ii) the connection strengths, which are known as synaptic weights, between interneurons are used to store the knowledge [6]. The neural network theory deals with learning from a previous obtained data, which is named as training or learning set, and then to check the system success using test data. In this study, artificial neural networks are used in the prediction of experimental processes in material science. An application of neural networks has been reported to design of a multi-component catalyst for methane oxidative coupling [7], and some sample papers have been given in [8,9]. The aim of this study to investigate prediction performance of various training algorithms using a neural network computer program for bending strength and hardness resistance of particulate reinforced (Al–Si–Mg)–MMCs. The results have shown that Levenberg–Marquardt learning algorithms gave the best result for this study.

2. Materials and experimental procedures

In this section, experimental processes have been explained with all the details which require producing some experimental data to use in the training and test set of the neural network (see Appendix A).

Al_2O_3/SiC powder mix was prepared from aluminium sulphate, ammonium sulphate and SiC aqueous suspension. This suspension was fired at 1200 °C for 2 h and highly porous Al_2O_3/SiC ceramic cake was obtained. This dual particle ceramic cake was milled and used as reinforcing particles for production of particle reinforced Al–Si–Mg alloy matrix composites. 10 vol% of these particle was mixed with molten aluminium between solidus and liquidus, then heated up and poured into dies to solidify composite samples.

Bending test of the cast composites carried out by a Dartec 94052 RK type testing machine at room temperature with 1 m/s speed. Test specimens were prepared. According to ASTM B-312 standard optical microscope (Olympus BH2-UMA) was used to examine particle distribution. The fractured surfaces were characterized by scanning electron microscope SEM (CamScan S4) and with attached EDS analysis at low (5 kV) voltage were used to investigate polish surfaces. The density measurement was performed by Archimedes principles using an electron balance. The porosity of composites was calculated as $1 - \rho_m/\rho_{th}$ where ρ_m and ρ_{th} are the measured and theoretical density, respectively. Scanning electron microscope image analyses of stir cast composite samples were made. The samples were polished and etched with Keller's solution before microscopic examination. Brinell hardness values of Al_2O_3/SiC particle aided MMCs materials were obtained by using Wolpert Testor HT1a type machine with 187.5 kg load and 2.5 mm dimensional steel ball at the end of 30 s.

Bending and hardness results which vary according to SiC particle size were used as an input data to train learning sets of neural network. After training learning sets of four different training algorithms. Output data were obtained for a neural network programs. The plots of input and output data were compared and best training algorithm way determined for mechanical properties of composites materials.

3. Microstructure and mechanical properties

At the end of the microscopic examination, as shown in Fig. 1, Al_2O_3/SiC particles were well dispersed in the matrix and fully wetted by molten aluminium. These particles are responsible for increase in mechanical properties. Silicon and magnesium 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 Fig. 1. This figure reveals that large particles with small Al_2O_3 particles reinforced MMC was successfully produced.

The results of three-point bending and hardness experiments have been given in Table 1. These results were also used input and output data for neural network training algorithms. The smallest resistance bending and hardness values have been obtained from coarse reinforced MMCs particles. With the decreasing of particle size the porosity, in spite of the increasing the porosity amounts in the composites structure, the bending resistance and hardness values have increased [10–12]. Recently, in the related studies [13–17], the decreasing in reinforcement particle size, improvement in bending resistance and hardness has been reported like the results given in Table 1. In these researches, having high resistance of reinforced thin particles MMCs had been based on the decreasing of reinforcement particles the cracking and breakings risk the situation of the high dislocation intensity and deformation.

As seen in Table 1, by the decreases on the particle dimension the bending and hardness resistance of MMCs have increased because of decreasing particle size and increasing number of particles in a unit volume. The fracture surfaces of the composites used in the bending experiments are given in scanning electron microscope (SEM) image in Fig. 2(a) and (b) oxygen and carbon peak do not exist in Al–Si–Mg matrix alloy from the elemental diffraction scanning (EDS) analysis, whereas in Fig. 3(a) and (b), these elements are present within the composites. Sliding type plastic deformations and dimples have been seen on the fraction surface. On the other hand, some cracked points have been observed on Al_2O_3/SiC particles in some regions. While the reinforcement particle size is decreasing, the cracks on the particles are getting clearer.

The microstructure of MMCs used in the experiments has been changed depending on cooling rate of casting. This cooling rate influences the distribution of Al_2O_3/SiC particles in the 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. The cooling speed affects the particle distribution in casting process

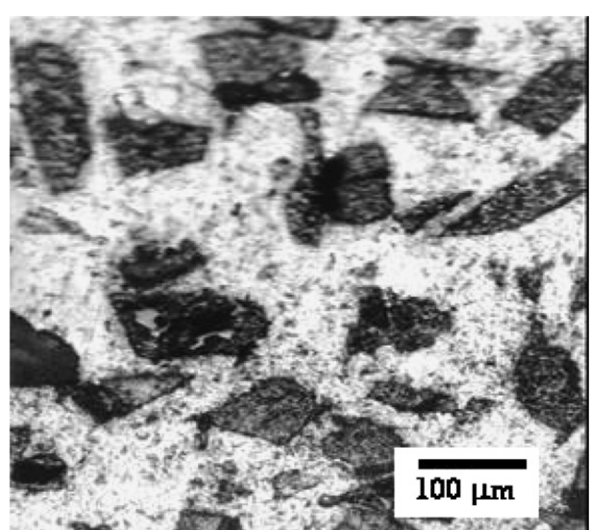

Fig. 1. Polish surface of SiC with Al_2O_3 reinforced MMC optical micrograph.

Table 1
The experimental data used to form the training and test sets

Samples used in training and test	Input of neural network	Output 1 of neural network	Output 2 of neural network
	Particle size (μm)	Bending strength (MPa)	Hardness (HB)
S(1)	2	481.2	118
S(2)	4	472.1	115
S(3)	8	461.3	111
S(4)	10	451.2	109
S(5)	16	448.8	107
S(6)	20	446.4	105
S(7)	27	441.5	103
S(8)	38	438.2	101
S(9)	45	421.3	98
S(10)	49	415.9	97
S(11)	53	410.4	96
S(12)	60	402.5	91
S(13)	67	395.1	86
S(14)	75	387.3	81
S(15)	87	378.3	77

and, so, hardness resistance has been affected. High cooling has caused the formation of small dendrites, and therefore, the nature of the vortex mechanisms described was reflected in the uniformity of the particle distribution. In vortex casting an almost uniform distribution of Al_2O_3/SiC particulates was achieved. In addition to this homogeny distribution, with decreasing of particle size the bending and hardness resistance of MMCs increased.

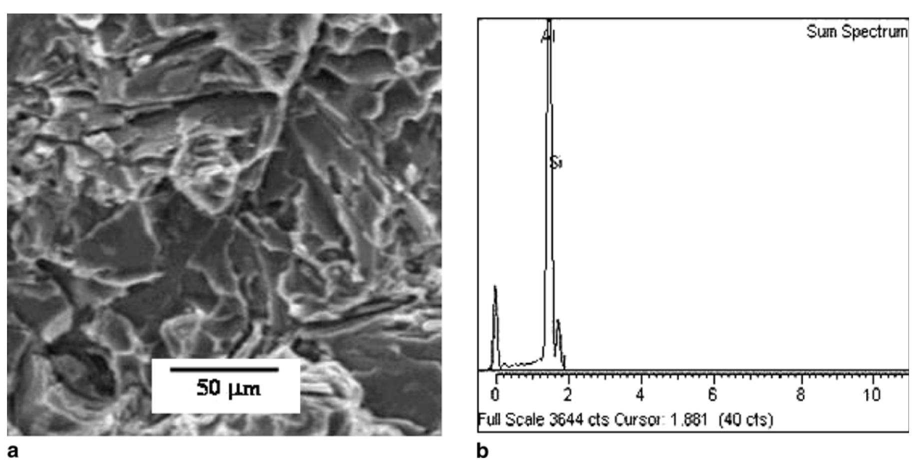

Fig. 2. (a) Fracture surface of A332 matrix alloy SEM micrograph and (b) EDS analysis.

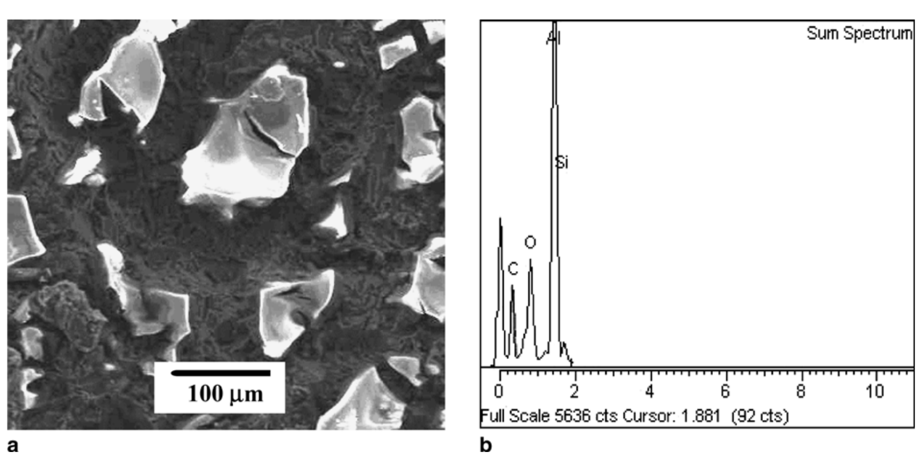

Fig. 3. (a) Fracture surface SiC with Al_2O_3 reinforced MMC and SEM micrograph and (b) EDS analysis.

4. Methodology of the prediction

Artificial neural networks concept, which is from artificial intelligence family, has been developed to model nonlinear processes in many areas. 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. It is self-adaptive to the environment so as to respond different inputs rationally [6,18]. In other word a desingned neural network can give quick response for any given input. Some advantages of a neural network are adoption, learning, generalization, ease implementation and self-organization [19]. Implementation of a neural network needs the decision of three main features: the structure in other words topology of the network, the type of activation function and learning algorithm. The structure of the network deals with the number of nodes in each layer, and the connection type between nodes. The activation function refers to the transfer function and discriminatory function (if there is) of each neuron, and the cost function of the network outputs. And the last one learning deals with using a learning algorithm and the parameters in that algorithm. There are a few learning algorithms such as gradient-descent and Levenberg–Marquardt.

According to the structure of a neural network in a problem solution, neural networks can be examined in two categories: feedback neural networks and feed forward neural networks. The most widely used algorithms are in general feed forward networks, which is simple from the viewpoint of structure and easily analyzed mathematically. The back propagation neural network scheme, which has a mathematically strong learning ability in training and mapping the relations between inputs and outputs, is a most commonly used network model [19].

Back propagation neural network are generally referred to as feed forwarded, multi-layered network with number of hidden layers and trained with a learning algorithm as shown in Fig. 4. Multi-layer preceptor (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 mean square error between the actual outputs of the network and the desired outputs in response to given inputs [20]. 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 (η) and momentum coefficient (α). 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 [18,21,22]. The neural network simulation, in this study, has been realized using neural network toolbox of Matlab. It selects the most suitable values for learning rate and momentum coefficient optimally. However, user in Matlab should define the number of neurons in the hidden layer.

The neuron shown in Fig. 5 can be classified into three types based on their inputs and outputs: input, output, hidden neurons. Input neurons are the ones that receive input from the environment, such as SiC particle size. 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.

The error is computed using Eqs. (1) and (2) known as average squared error [18]. 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

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

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

Lastly, the input value is passed through the neural network again with updates new weights, and the errors, if any, are calculated again. This technique is iterated until the error is acceptable. This method is continued for all the data in the training data. Finally, the test data are used to verify the non-linear relationship between the input and output data sets [23,24].

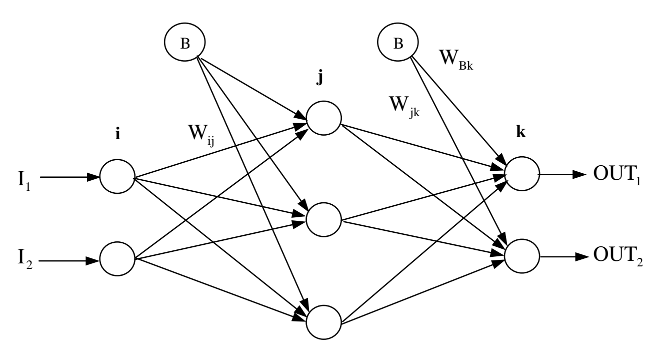

Fig. 4. A sample multi-layer feed forward net structure.

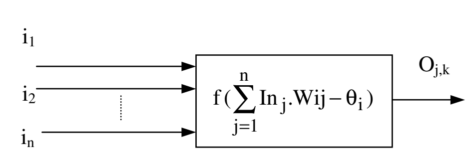

Fig. 5. Neuron structure.

4.1. Neural network training algorithms

Recently, artificial neural networks are used as an interdisciplinary tool in many type of nonlinear problem solution. To design a neural network for a problem solution needs a training algorithm. It is necessary to prepare a set of examples, which represents the problem in the forms of system inputs and outputs. During the training process, the weights and biases in the network are adjusted to minimize the error to obtain a high-performance in the solution. At the end of training and during the training error, mean squared error is computed between desired outputs and target outputs. There are various training algorithms used in neural network applications. It is hardly difficult to predict which of these training algorithms will be the fastest one for any problem [25]. Generally, it depends on some factors; the structure of the networks, in other words, the number of hidden layers, weights and biases in the network, aimed error at the learning, and application area, for instance, pattern recognition or classification or function approximation problem. However, the data structure and uniformity of the training set are also important things that affect the system accuracy and performance. In this article, four different training algorithms were used in the prediction of experimental results.

The reason of the difficulty in the training algorithm is the presence of the multiple points including multiple minima. The training algorithms are usually based on Taylor's series, but the presence of the multiple points, including local minima makes difficult and complicated the analyses due to the fact that it is needed to be convinced about converging to the same local minimum as used in the expansion. In practice, four types of optimization algorithms that are used to minimize the error exist. The first three methods, general optimization methods, are gradient descent, conjugate gradients and quasi-Newton. The operation of these general optimization methods can be comprehended in the context of minimizing a quadratic error function. In spite of the fact that the error surface is certainly not quadratic, it will be so in a sufficiently small neighbourhood of a local minimum for differentiable node functions such an analysis gives information about the attitude of the learning algorithm over the period of a few iterations and also as it comes closer to its goal. However, the fourth method, Levenberg–Marquardt is especially adapted to the minimization of an error function, which comes out from a squared error criterion of the assumed form [26].

In this study, the prediction of bending strength and hardening behaviour of particulate reinforced (Al–Si–Mg)–MMCs have been analysed using various training algorithms. The used training algorithms are Levenberg–Marquardt, quasi-Newton, resilient back propagation, and variable learning rate back propagation. During the study, the prepared training and test sets were examined for each training algorithm to evaluate their performances. The fundamental principles of each training algorithm were given in the next section. The aim of this paper is to investigate the training performance of the neural network for mentioned training algorithms.

4.1.1. Levenberg–Marquardt (LM)

Many researchers [27,28] have used the MLP with the LM learning algorithm to track a full azimuthally sector with only three array elements. One hidden layer of the MLP is composed of Adaline neurons. The LM algorithm is much faster but requires more memory than the BP rule. The authors in [28] have used two parallel MLP's and a subsequent Kohonen network [29,30]. Similarly with quasi-Newton a method, the Levenberg–Marquardt method is based on approaching second-order training speeds without having the computation of Hessian matrix, in other words, second derivatives [31,32]. The advantage of this training method is its convergence about minimum and giving more accurate results. The unique difficulty of using Levenberg–Marquardt algorithm is the requirement of more memory than the traditional back propagation method [33]. The Levenberg–Marquardt training algorithm was found to be the fastest training algorithm, however it requires more memory with the same error convergence bound compared to training methods [34].

4.1.2. Quasi-Newton (QN)

Normally, Newton's method is an alternative to the conjugate gradient methods especially fast optimization. The fundamental step of this algorithm is where are the second derivatives of the performance index at the present values of the weights and biases on the network. The convergence of Newton's algorithm is frequently faster than conjugate gradient descent methods. However, the computation of second derivatives is complicated in Newton's method. To overcome this computational complexity, the quasi-Newton, which does not need the computation of second derivatives, is developed based on Newton's method. The principle of quasi-Newton algorithm is based on updating an approximate Hessian matrix at each iteration. The update is calculated as a function of the gradient [35,36].

4.1.3. Resilient back propagation (RBP)

Feed forward multiplayer neural networks generally use sigmoid activation function in the hidden layer. Activation function squashes an infinite input range into a finite output range. The characterization of a sigmoid activation function can be defined as that their slope must come closer to zero the inputs value takes large value. Therefore, a problem occurs when steepest descent is used to train a multiplayer neural network including sigmoid activation functions, because the magnitude of the gradient can take very small values. So, small changes in the weights occur, although the weights are far from the optimal values that they should have. To overcome this problem, resilient back propagation algorithm (RBP) was generated. Main aim of RBP is to remove the mentioned unwanted effects of the magnitudes belonging partial derivatives [37].

4.1.4. Variable learning rate back propagation (VLRBP)

In the training process of a neural network, the learning rate is fixed as a constant with standard steepest descent. To obtain high-performance learning in the training also depends on the appropriate setting of the learning rate. Setting learning rate too high or too low, the training process can oscillate and take too much time for the convergence. In practice, it is very difficult to decide the optimum value for learning rate parameter, however, the optimum value of learning rate changes during the training process.

In VLRBP algorithm, the performance of the steepest descent algorithm can be improved based on changing learning rate value during the learning process. To keep the training step size as large as possible while keeping training stable, as adaptive learning rate will be examined. The learning rate parameter is gotten responsive to the complexity of the local error. The learning rate value is increased, however, only to improve that the neural network can learn without large error increments. So, a learning rate value that is near optimal will be obtained locally. Summarizing the VLRBP, when a larger learning rate can give results with stability, the learning rate will be increased, on the other hand, when the learning rate is too high to warrant an error decrease, it will be got decreased until a stable learning is observed [31,38].

5. Neural network design

In this study, the neural network is used to predict bending strength, hardening behaviour of particulate reinforced (Al–Si–Mg)–MMCs. In the design of a neural network, training and test sets have been prepared using some data experimentally obtained (Table 1). As sigmoid activation function is used in each training algorithm, all numbers in training and test sets have been normalized between 0 and 1 because of its characteristic feature. Feed forward neural networks were used in all cases. For each training algorithms, the following steps can be listed as: (i) constituting the database for training and test processes of neural networks for each training algorithms; (ii) analysis and normalization of the data; (iii) training of the neural network using each training algorithm; (iv) testing of the trained networks; and (v) employing the trained neural networks for prediction.

In the analysis of performance of various training algorithms, the same prepared learning and test set were used in the training processes of each learning algorithm. The performance analysis were done from the viewpoint of training duration, error minimization and prediction achievement. Then, each training processes results were interpreted with graphics in this paper.

A neural network is implemented with three layer feed-forward structure with an input layer, a hidden layer and an output layer. The designed neural network has 1 input and 2 output neurons (Fig. 6). Number of neurons in the hidden layer for each training algorithm was selected during the simulation experimentally.

Each designed neural networks using various training algorithms were tested by those ways: (i) Using the test data, which were not used during the training procedure. Because of that during the training process neural network used the training set and had information about the characteristic of the data in training set. It is clear that the neural network will give the better result for any data in training set than for any data in test set. (ii) Mean square error (MSE), which is statistical and scientific error computation method, was used to analyze the error. (iii) The neural network predictions were directly compared with the experimental obtained data to evaluate the learning performance.

In Fig. 7, obtained MSE values for training data were given for each training algorithm. The obtained error values for different number of neurons in the hidden layer were analyzed and given, graphically. This figure also gives information about the accuracy of each training algorithm depending on the number of neurons in the hidden layer. It is evident from this figure; the least error value was obtained by using Levenberg–Marquardt training algorithm. MSE is a good criterion to have information about learning performance. The iterations were continued until it is decided that the minimum MSE error is obtained (Fig. 7). It is obviously seen that the most minimum MSE value was obtained with Levenberg–Marquardt training algorithm including eight neurons in the hidden layer. Quasi-Newton with 10 neurons in the hidden layer follows Levenberg–Marquardt algorithm, and thirdly VLBP including six neurons in the hidden layer has clearly much error than the previous two ones. The much error was obtained from the RBP training algorithm.

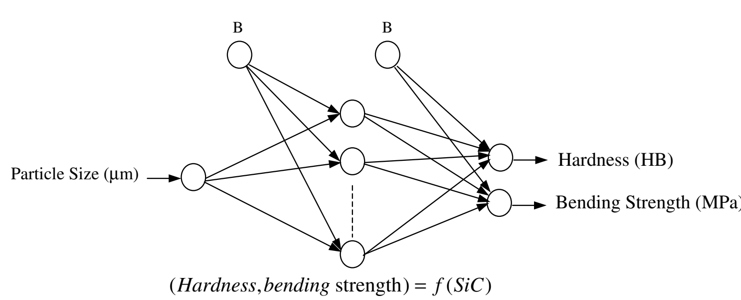

Fig. 6. The topology of involved neural networks.

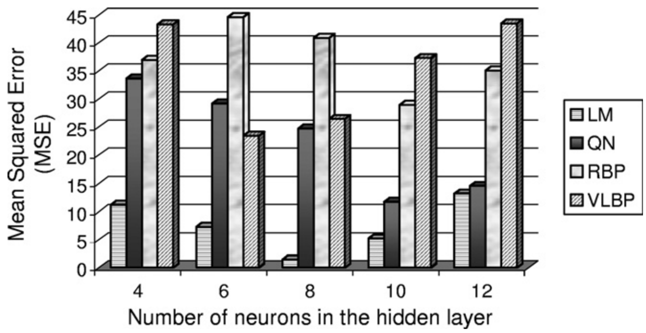

Fig. 7. Evaluation of the training performance of the networks for different training algorithms according to MSE values.

Since implementation of these training algorithms is indeed very time consuming processes. It is important to be convinced about that the obtained solutions are optimum one. Therefore, the error behaviour of the neural network has to be observed to find the results with minimum errors. There is no known concept about selection of the number of neurons in the hidden layer. The neuron number in the hidden layer can be found experimentally. That is why finding the minimum number in of neuron, the hidden layer to obtain the results with minimum errors takes too much time because of the computations for each different neuron number in the hidden layer. In Fig. 7, MSE error values are computed and given at the end of training process for each algorithm.

In Fig. 8, the change of MSE values for each training method is given for the first 10^3 s. The speed advantage of the Levenberg–Marquardt method is evidently seen. Normally, it has the computational complexity, however it can give the results with much accuracy and in the less number of iterations than other methods.

The computation time of the training algorithm is important in artificial neural network based applications. In this study, it was proven that the LM learning algorithm based on a non-linear least squares optimization technique is significantly efficient in the training of a neural network. In spite of the fact that the necessary computations for this algorithm is more than those of the back propagation algorithm, its convergence speed makes it more preferable algorithm in many neural network applications [39].

6. Predictions results of the composites properties

In Table 2, the experimental and neural network prediction results of bending strength are given as a comparison of the training algorithms. From the prediction results, the predictions obtained from QN and VLBP are found closer, and the error in their predictions is slightly lower than RBP. On the other hand, LM training algorithm's prediction results are found better than others.

In Table 3, the experimental and neural network prediction results of hardness behaviours are given. Here, maximum error is observed in the predictions of RBP method. Minimum error is seen with VLPBP training method. Predictions of LM and QN are found similar and the closest results are observed using LM method.

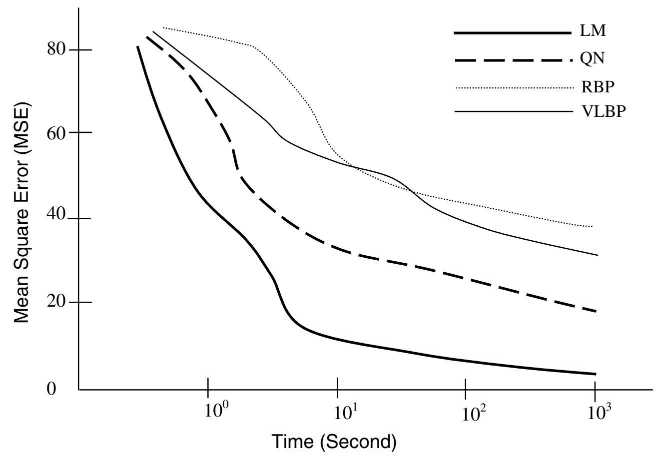

Fig. 8. Comparison of MSE error curves versus training time for each learning method.

As stated above, the predictions for test set is very important about the evaluation of the neural network prediction performance. In this section, the test data for bending strength and hardness were used to evaluate the prediction results. The curves showing the neural network predictions and experimental values of test data were given in Figs. 9 and 10 for bending strength and hardness, respectively. The sum of MSE errors for the training and test data indicates the accuracy of each training method. According to the testing results, the predictions of Levenberg–Marquardt method are better then obtained results using other training algorithms.

In Fig. 9, the curves of experimental results and neural network predictions of bending strengths versus particle size for each training methods were given for each training algorithm. Fig. 9(a) reveals that the results obtained experimentally and predictions of by LM. It is clearly seen that the experimental and prediction data are in a good accord. In Fig. 9(b), the test results for QN method was given, and the experimental results and neural network prediction data were found closer, however some small errors were

Table 2
The neural network bending strength prediction results of training set for different training algorithms

Samples	Particle size (μm)	Experimental bending strength (MPa)	Neural network results for various training algorithms			
			LM	QN	RBP	VLBP
S(1)	2	481.2	481.3	480.6	482.3	480.4
S(3)	8	461.3	461.1	461.6	461.7	461.7
S(4)	10	451.2	451.3	453.7	450.2	450.1
S(6)	20	446.4	446.2	445.5	444.2	447.9
S(7)	27	441.5	441.3	442.5	441.9	441.1
S(8)	38	438.2	438.4	438.9	438.8	439.9
S(9)	45	421.3	421.5	421.7	419.2	422.9
S(11)	53	410.4	409.8	409.3	411.7	409.1
S(12)	60	402.5	402.7	401.2	404.8	401.2
S(14)	75	387.3	387.4	385.9	388.2	387.7

Table 3
The neural network hardness prediction results of training set for different training algorithms

Samples	Particle size (μm)	Experimental hardness (HB)	Neural network results for various training algorithms			
			LM	QN	RBP	VLBP
S(1)	2	118	118.1	118.3	119.6	116.7
S(3)	8	111	111.4	112.3	112.6	111.3
S(4)	10	109	109.2	109.3	109.3	107.3
S(6)	20	105	105.3	105.9	104.1	106.2
S(7)	27	103	102.8	101.9	103.9	103.9
S(8)	38	101	100.6	100.3	100.9	102.3
S(9)	45	98	97.5	97.7	98.6	98.4
S(11)	53	96	95.9	97.2	96.7	95.2
S(12)	60	91	91.1	91.3	90.2	91.9
S(14)	75	81	80.9	80.2	82.4	80.2

seen between the curves on the graph. Likewise, in Fig. 9(c), the test results of RBP were similar to the experimental data, however some errors were observed on the curves. Lastly, in Fig. 9(d), the experimental and VLSP prediction results were indicated. It can be interpreted like Figs. 9(b) and (c), namely, the results experimental and VLSP were found closer, but some errors were observed. The accuracy of each algorithm was evaluated by using the test data set and MSE for bending strength. For both evaluations, it is evidently seen that LM training method has given the best results.

Similarly, the curves of experimental and prediction values of hardness were given in Fig. 10. Generally, the prediction results hardness tests have more error than the bending strength. Fig. 10(a) shows the prediction results obtained by using LM training technique, and in spite of the much error observed in the prediction of other three training methods, LM has given the best results as it can be seen that both curves are closed to each other in the graph. In Fig. 10(b), the prediction of QN and experimental results curves are shown, and there are some errors locally in the data. In Fig. 10(c), the curves were drawn using experimental and the results obtained from RBP training algorithm. The predictions of RBP have many errors points on all data. In Fig. 10(d), the prediction results for VLSP training algorithm were given. Its results were found similar with the results obtained with using RBP, in other words, there are many error in the graph. For the prediction of hardness, the accuracy of LM training algorithm can be clearly observed in Fig. 10(a).

The error for the training and test sets were computed and given in Table 4. MSE is a good criterion in the eval-

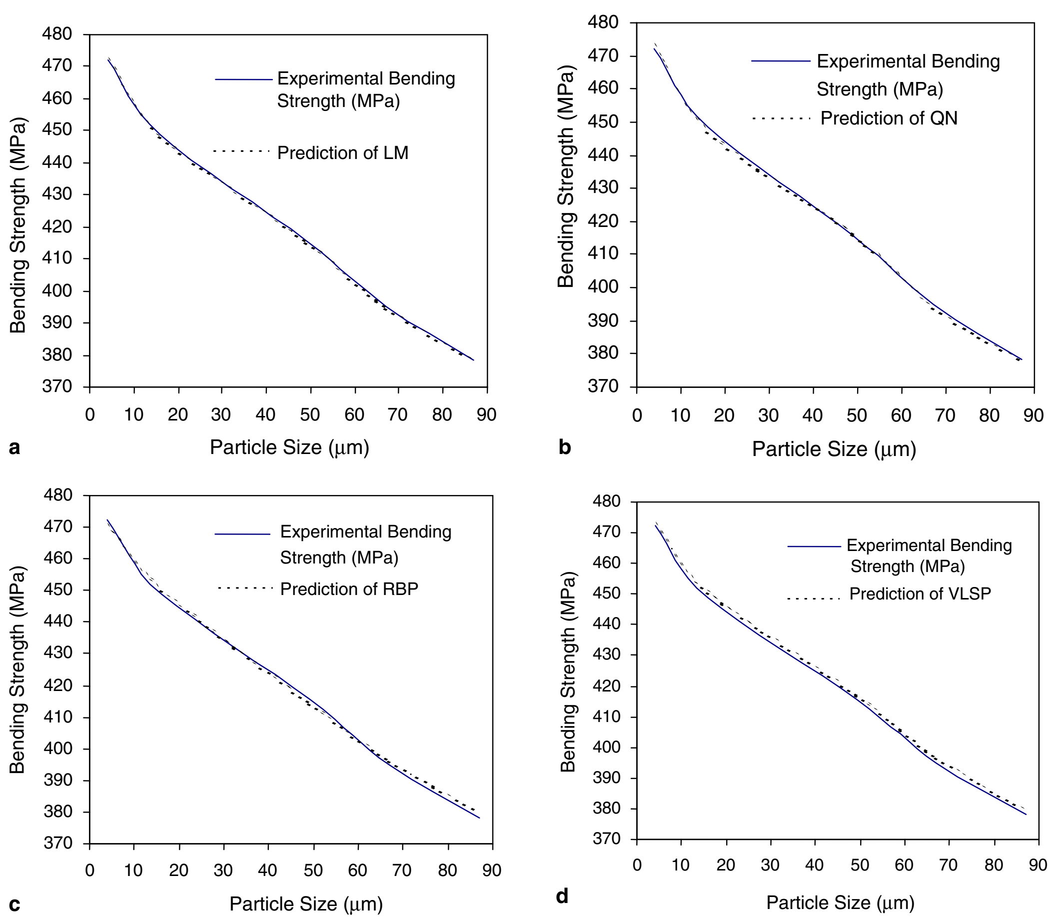

Fig. 9. The curves of experimental results and neural network predictions of bending strengths versus particle size for each training methods: (a) LM training predictions, (b) QN training predictions, (c) RBP training predictions, and (d) VLSP training predictions.

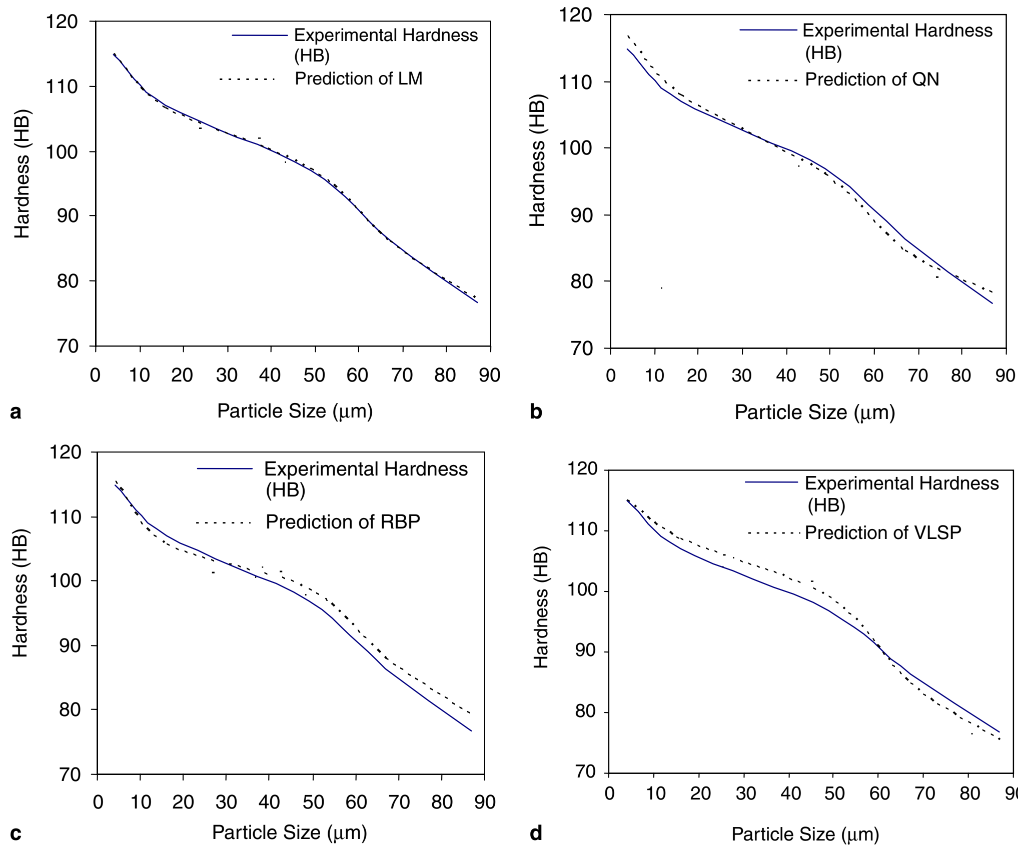

Fig. 10. The curves of experimental and neural network results of hardness versus particle size for each training methods: (a) LM training predictions, (b) QN training predictions, (c) RBP training predictions, and (d) VLSP training predictions.

uation of results of a neural network based application. The error values were computed using MSE using Eqs. (1) and (2). According to the error values observed at the end of learning, Levenberg–Marquardt results better than other training methods.

7. Discussion

In this study, the effects of the various training algorithms on the prediction of performance of an experimental process have been analyzed. Four different training algorithms ware examined in the training process, and their prediction results were presented in Tables 2 and 3 and Figs. 9 and 10.

The result obtained from the experimental processes showed that when the solidification-cooling rate decreased, the crystalline grain size of the matrix alloy and the eutectic silicon phase increased gradually, but the bending strength and hardness decreased. Fracture surfaces of the MMCs broken and cleaved Al_2O_3/SiC particles were observed on the fracture surfaces of the composites [39].

Table 4
MSE error values obtained for training and test sets

Training algorithms	MSE errors	
	For training set	For test set
LM	1.46	1.54
QN	21.73	15.57
RBP	29.83	22.42
VLBP	25.78	21.37

Mechanical tests revealed that bending strength and hardness resistance of 10 vol% Al_2O_3/SiC dual ceramic powder composites decrease with increasing reinforced SiC particle size. To say about the bending and hardness experiments, the composites having big particles tend to crackling under mechanical forces, indicating lower bending and hardness resistance. Because of that dislocation movement is inhibited, and figure changing becomes difficult while particle size is decreasing. This feature has increased the bending and hardness resistance values. Finally, maximum bending values have also been obtained for MMCs, like obtained maximum hardness value. Mingyuan et al. [40] has reported that for particle reinforced composite with molten Al and alloying elements seggregated in the interface to improve the wetting characteristics and the bonding strength between the particles and the Al matrix. It is beneficial for the particles to facilitate incorporation with and the uniform distribution in the matrix alloy, and to improve the strength and ductility of the composite.

Later than time consuming studies based on training of a back propagation neural network using various learning algorithms, a neural network has been designed to predict the results of an experimental process. It is concluded that considerable savings in terms of cost and time could be obtained from using neural network model. It is also concluded that ANN is a successful analytical tool if properly used. The selection of training algorithm is mostly important in these kinds of studies. In the study, the best prediction results have been obtained with Levenberg–Marquardt training algorithm according to Tables 2 and 3 and Figs. 7–10. On the other hand, other learning algorithms have also given prediction results with an acceptable error. But, the predictions obtained from the trained network with Levenberg–Marquardt were found with the minimum error in the results of each training algorithms, namely, the best results were obtained with Levenberg–Marquardt. However, It is very difficult to generalize which training algorithm will be the fastest for any given problem. It can depend on the complexity of the problem. But, the results for the data set used in this study have shown that Levenberg–Marquardt algorithm gave the best results. For the predictions in this paper, amongst various training algorithms, it is confirmed that the Levenberg–Marquardt training method is the fastest converging one, and working with high accuracy in prediction.

8. Conclusions

In this study, the effect of various training algorithms on learning performance of the neural networks on the prediction of bending strength and hardness behaviour of particulate reinforced (Al–Si–Mg)–MMCs were investigated. Additionally, the effect of number of neurons in the hidden layer was also examined. The basic consideration of this study is to predict the result of the bending and hardness experiments of Al_2O_3/SiC reinforced MMC. It is practical to use realized experimental values instead of time consuming experiments. The neural network prediction results showed a good agreement with experimental results for each training method. In other words, resulting prediction values were found acceptable for each training method. However, it is confirmed that the Levenberg–Marquardt training algorithm was found the fastest converging one and working with high accuracy in prediction.

As a result, considerable savings in terms of cost and time were gained by using neural network model. Neural network results revealed a good accord with experimental data, and neural network supplied more beneficial data from comparatively small experimental databases. Furthermore, very good performance can be achieved by using the most suitable training algorithm of the neural network. It is very difficult to generalize which training algorithm will be the fastest one for any given problem. For this study, the Levenberg–Marquardt training algorithm gave better and faster results than other ones. According to the obtained prediction results and MSE values for training and test sets, the superiority of this algorithm evidently seen.

Appendix A

The obtained prediction values for training set is closer to the experimental data than obtained for the test data. Therefore, the prediction results for training set were given in the paper. However, the prediction results for test set naturally have much error according to the training set, and can be observed graphically. In the text, the prediction results for test set were presented with graphics. The obtained prediction values for test data set were also given in Tables A1 and A2.

Table A1
The neural network bending strength prediction results of test set for different training algorithms

Samples	Particle size (μm)	Experimental bending strength (MPa)	Neural network results for various training algorithms			
			LM	QN	RBP	VLBP
S(2)	4	472.1	472.3	473.1	470.7	472.9
S(5)	16	448.8	448.2	447.1	449.9	450.6
S(10)	49	415.9	415.3	416.2	414.4	417.2
S(13)	67	395.1	394.7	394.1	396.4	396.7
S(15)	87	378.3	378.5	377.7	379.8	379.5

Table A2
The neural network hardness prediction results of test set for different training algorithms

Samples	Particle size (μm)	Experimental hardness (HB)	Neural network results for various training algorithms			
			LM	QN	RBP	VLBP
S(2)	4	115	115.1	116.8	115.5	115
S(5)	16	107	106.6	107.8	105.7	108.6
S(10)	49	97	97.2	96.1	98.6	99.2
S(13)	67	86	86.1	84.5	87.9	84.7
S(15)	87	77	77.2	78.3	79.1	75.5

References

[1] Kang CG, Kim NK, Kim BM. J Mater Process Technol 2000;100:53–62.
[2] Lin YC, Li HC, Liou SS, Shie MT. Mater Sci Eng A 2004;373:363–9.
[3] Hemanth J. Mater Design 2001;22:375–82.
[4] Seshan S, Jayamathy M, Kailas SV, Srivatsan TS. Mater Sci Eng A 2003;363:345–51.
[5] Ganesan G, Raghukandan K, Karthikeyan R, Pai BC. Mater Sci Eng A 2004;369:230–5.
[6] Haykin S. Neural networks. New York: Macmillan College Publishing Company; 1994. p. 138.
[7] Huang K, Chen F-Q, Lu DW. Artificial neural network-aided design of a multi-component catalyst for methane oxidative coupling. Appl Catal A 2001;219:61–8.
[8] Genel K, Özbek İ, Kurt A, Bindal C. Boriding response of AISI W1 steel and use of artificial neural network for prediction of borided layer properties. Surf Coat Technol 2002;160(1):38–43.
[9] Chun MS, Biglou J, Lenard JG, Kim JG. Using neural networks to predict parameters in the hot working of aluminium alloys. J Mater Process Technol 1998;86(1–3):245–51.
[10] Gui MC, Wang DB, Wu JJ, Yuan GJ, Li CG. Microstructure and mechanical properties of cast (Al–Si)/SiC_p composites produced by liquid and semisolid double stirring process. Mater Sci Technol 2000;16(5):556–63.
[11] Kamat SV, Manoharan M. Work hardening behaviour of alümuna particulate reinforced 2024 aluminium alloys matriks composites. J Comput Mater 1993;27:1714–21.
[12] Eardley ES, Flower HM. Infiltration and solidification of commercial purity aluminium matrix composites. Mater Eng A 2003;359:303–12.
[13] Brechet Y, Embury JD, Tao S, Luo L. Damage initiation in metal matrix composites. Acta Metall Mater 1991;39(8):1781–6.
[14] Weng BJ, Chang ST, Shiau JS. Micro-fracture mechanisms of SiC-6061 aluminium composite after hipping. Scripta Metall Mater 1992;27(9):1127–32.
[15] Arsenault RJ, Wang L, Feng CR. Strengthening of composites due to micro-structural changes in the matrix. Acta Metall Mater 1991;39(1):47–57.
[16] Yang Y, Cady C, Hu MS, Zok P, Mehrabian R, Evans AG. Effects of damage on the flow strength and ductility of a ductile Al alloy reinforced with SiC particulates. Acta Metall Mater 1990;3812:2613–9.
[17] Hunt Jr WH, Osman T-M, Lewandowski J-J. Micro- and micro-structural factors in DRA fracture resistance. JOM 1993;45:30–5.
[18] Altinkok N, Koker R. Neural network approach to prediction of bending strength and hardening behaviour of particulate reinforced (Al–Si–Mg)–aluminium matrix composites. Mater Design 2004;25:595–602.
[19] Jain RK, Jain VK, Kalra PK. Modelling of abrasive flow machining process: a neural network approach. Wear 1999;231:242–8.
[20] Cakar T, Cil I. Artificial neural networks for design of manufacturing systems and selection of priority rules. Int J Comput Integrat Manuf 2004;17(3):195–211.
[21] Çetiner BG, Haşiloğlu AS, Bayramoğlu M, Köker R. Comparative study of texture classification using various wavelet schemes. In: Proceedings of the second international symposium on IMS, Turkey; August, 1998. p. 709–16.
[22] Köker R, Öz C, ve Ferikoğlu A. Development of a vision based object classification system for a robotic manipulator. In: Proceedings of the eighth IEEE international conference on electronics, circuits and systems, vol.3; 2001. p. 1281–4.
[23] Timothy JR. Fuzzy logic with engineering applications. New York: McGrow-Hill; 1995.
[24] Wasserman PD. Neural computing. New York: van Nostrand-Reinhold; 1989.
[25] Charpentier E, Laurin JJ. Sectorial direction finding antenna array with a MLP beam former. In: Proceedings of the IEEE international symposium on antennas and propagation, vol. 4, Montreal, Canada; July, 1997. p. 2270–3.
[26] Abraham A. Meta learning evolutionary artificial neural networks. Neurocomputing 2004;56:1–38.
[27] Charpentier E, Laurin JJ. An implementation of direction ending antenna for mobile communications using a neural network. IEEE Trans Antenna Propagat 1999;47(7):1152–9.
[28] Kohonen T. The self-organizing map. Proc IEEE 1990;78:1464–80.
[29] Du KL, Lai AKY, Cheng KKM, Swamy MNS. Neural methods for antenna array signal processing: a review. Signal Process 2002;82:547–61.
[30] Malinov S, Sha W, Keown Mc. Application of artificial neural networks for modelling correlations in titanium alloys. Mater Sci Eng A 2004;365:202–11.
[31] Hagan MT, Demuth HB, Beale MH. Neural network design. Boston (MA): PWS Publishing; 1996.
[32] Hagan MT, Menhaj M. Training feed forward networks with the Marquardt algorithm. IEEE Trans Neural Networks 1994;5(6):989–93.
[33] Karkoub M, Elkamel A. Modelling pressure distribution in a rectangular gas bearing using neural networks. Tribol Int 1997;30(2):139–50.
[34] Hagan MT, Menhaj MB. Training feed forward networks with the Marquardt algorithm. IEEE Trans Neural Networks 1994;5(6):989–93.
[35] Dennis JE, Schnabel RB. Numerical methods for unconstraint optimization and nonlinear equations. Englewood Cliffs (NJ): Prentice Hall; 1983.
[36] Battiti R. First and second-order methods for learning: Between steepest descent and Newton's method. Neural Comput 1992;4(2):141–66.
[37] Riedmiller M, Braun H. A direct adaptive method for faster back propagation learning: The RPROP algorithm. In: Proceedings of the IEEE international conference on neural networks; 1993. p. 896.
[38] Matlab@ Documentation, version 6.5, release 13, the Mathworks, Inc., 2002.
[39] Safak KK, Turkay OS. Experimental identification of universal motor dynamics using neural networks. Mechatronics 2000;10:881.
[40] Mingyuan G, Yanping J, Zhi M, Zengan W, Renjie W. Effects of reinforcement oxidation on the mechanical properties of SiC particulate reinforced aluminum composites. Mater Sci Eng A 1998;252(2):188–98.