

Age Hardening Process Modeling and Optimization of Aluminum Alloy 8011/SiC Particulate Composite for Brake Drum Application using RSM and ANN

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Abstract

Most conventional ceramic based aluminum metal matrix composites (MMCs) are either heavy, costly or combination of both. In order to reduce cost and weight, while at the same time maintaining quality, silicon carbide particles (SiCp) was used with aluminum alloy 8011 to produce MMC for brake drum application and other engineering uses. The aim of this research is to model the age hardening process of the produced composite using response surface methodology (RSM) and artificial neural network (ANN), for optimization of age hardening process parameters. The results show that ANN modeled the age hardening data excellently and better than RSM with a correlation coefficient of experimental response with ANN predictions being 0.9921 as against 0.9583 for the RSM. The optimized process parameters were in very close agreement with the experimental values with the maximum relative error of 1.2%, minimum of 0.35%.

Keywords: Artificial neural network, Heat treatment process, Stir casting method, Mechanical properties.

1. INTRODUCTION

Neural networks have been applied in every area for solving various materials related

Problems such as design and development, processing and controlling of materials, products and equipment. This technique has also been effectively applied by many of investigators in the field of materials

The applications of neural networks modeling was adopted by Badeshah [1], Shah, I., [2], and Genel, et. al. [3] who had well documented neural networks applications in materials science concerned with the micro structural evaluation of steels, processing and properties of steels as well as conducted study on ductile cast iron. The materials science based work using neural networks which had brought attention of researchers recently conducted by Sha and Edwards [4].

Micro structural features such as amount of austenite retained in ductile austempered cast iron was estimated by Yascas, et. al. [5] using artificial neural networks. The features classification of alloy steel microstructures consist ferrite and pearlite was investigated using back propagation algorithm which can effectively be used for the features classification by

Martin and William [6]. The microstructure image analysis of complex systems have been determined by using neural networks technique as reported by Maly, Harck and Novotny [7].

In the field of powder metallurgy neural networks had been successfully applied by Sudhakar and Hague [8], Ohdar and Pasha [9], and Jokhio, M.H., et. al. [10] in determining the mechanical properties and processing parameters. Many of investigators such as Kowalski, et. al. [11], Dobrzanski and Sitech [12] applied neural networks modeling in processing of steels and determining their performance as well as characterization involving the complex analysis of problems.

The materials performance depends on the complex materials, interrelated factors including chemistry and processing method whereas, experimental observations could not capture all materials aspects. Material development, processing and characterizations are timed consuming and difficult tasks. However, neural networks have the capability in capturing the experimentally observed behavior through a learning process Jokhio, M.H., [13-14].

2. EXPERIMENTAL PROCEDURE

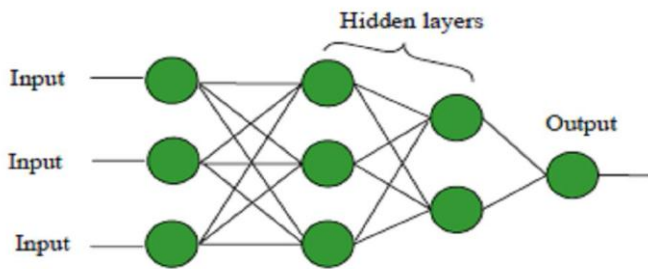
8011 aluminum alloy was used as the metal matrix and 10%SiC particles as the reinforcement. The metal matrix consists of (in weight percentage) 0.625 Si, 0.725 Fe, 0.007 Cu, 0.003 Mn, 0.002 Mg, 0.013 Ti, 0.001 Cr, 0.002 Zn and rest being aluminum. The reinforcement size used in the composites was 23 μ m. The composites were manufactured through stirring casting technique under an argon atmosphere. The melt was cast into a permanent die, to obtain ingots of 35mm diameter and 70mm height after the feeder head was removed. The cylindrical ingots were machined to 30mm diameter, and then hot extruded in four stages to obtain 16mm diameter rod. The forming process was performed at 500°C. During the extrusion process the punch speed was 0.01 m/s and graphite based high temperature lubricant was used. The extruded rods were solution heat treated for 3h at 530°C followed by cold water quenching to room temperature. Then the rods were artificial aging at different temperature (130°C to 210°C) over time period for (1-9) hours. Tensile test specimens were prepared according to ASTM-E8M standard. The length and diameter of the gage were 45mm and 9mm respectively. Tensile tests were conducted using a universal

testing machine. The hardness measurements were performed using a microhardness tester with a load of 500 kgf. Hardness values were averaged over three measurements taken at different points on the cross-section. The variation of hardness with aging time for different aging conditions was investigated. Sample specimens for microstructural examinations were prepared following standard procedure of grinding and polishing by etching in keller’s reagent. Optical microscopy was performed to evaluate the distribution of SiC particles. The fracture surface of the composite was also examined using SEM. For modeling and prediction of hardness, tensile strength, yield strength, and modulus of elasticity, a forward and backward feed propagation multilayer artificial neural network was developed to evaluate and compare the experimental calculated data to predict values.

3. RESULTS AND DISCUSSION

3.1 ARTIFICIAL NEURAL NETWORK

Neural network architecture made up of inputs, network layers with hidden layers and output is shown in Fig. 1. At the training stage, the data was given to the network. The network computes an output which is compared to the desired output. Based on the level of error (difference between computed output and desired output) referred to as cost in neural network terms, the network weights are modified (adapted) to reduce the error. The weight modification is done by passing the epoch through an iteration process. An epoch is a complete set of input/output data made up of elementary. The weight modification is done by passing epoch through an iteration process[15,16].



3 Inputs :solutionizing time, Aging temperature, aging time
 1 Output : Tensile strength

Fig. 1 A neural network architecture [adapted]

3.2 TRAINING USING MULTILAYER PERCEPTRON NEURAL NETWORK TYPE

Multilayer perceptrons (MLP) are layered feed forward network architecture which is typically trained with static back propagation. In this network architecture there are 3 input processing elements (solutionizing time, aging temperature , aging time), 1 output processing element (Tensile strength), 20 exemplars and 1 hidden layer. The hidden layer has 16 processing elements, TanhAxon transfer function with momentum learning rule. The output layer uses

BiasAxon transfer function with conjugate gradient learning rule. The hidden layer and the process elements were determined by trial and error and by comparing the error output. The generated network architecture is shown in Fig. 2

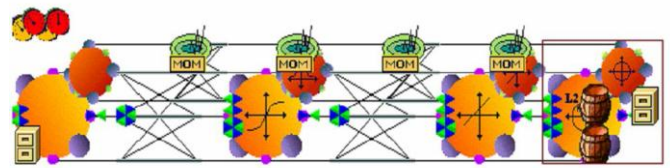


Fig. 2 Generated multilayer perceptrons (MLP) network architecture design

These values were then compared to the actual values of the target variables for this training set observation and the errors are calculated. Normalized root mean square error value (NSE) was used to evaluate the training performance of the ANN.

$$NSE = \sqrt{\frac{\sum(\theta - \theta_0)^2}{\sum\theta^2}}$$

Where θ is the experimental mass loss in tensile and θ_0 represents the predicted output value for tensile strength. It is important to evaluate the performance of the ANN model. This was done by separating the data into two sets: the training set and the testing set. The parameters (i.e., the value of weights) of the network were computed using the training set. When reaching the error goal, the learning process was stopped and the network was evaluated with the data from the testing set [17].

3.3 VERIFICATION OF TRAINED NEUTRAL NETWORK

From this Fig.3 performance training is achieved after 511.2486 iteration with MSE error of 0.2 and 6 validating checks. The R-value for the training data is at 0.99784 and the R-value for the testing data is 0.99591 for 8011 Al/15%SiCp composites. The performance training is achieved after 904.93 iteration with MSE error of 0.1 and 7 validating checks

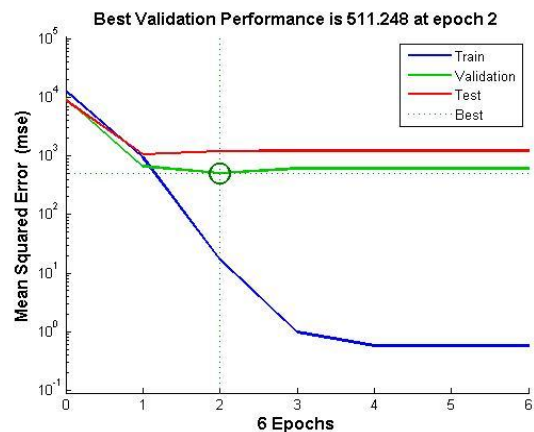


Fig 3 Performance curve for the 8011Al/15%SiCp

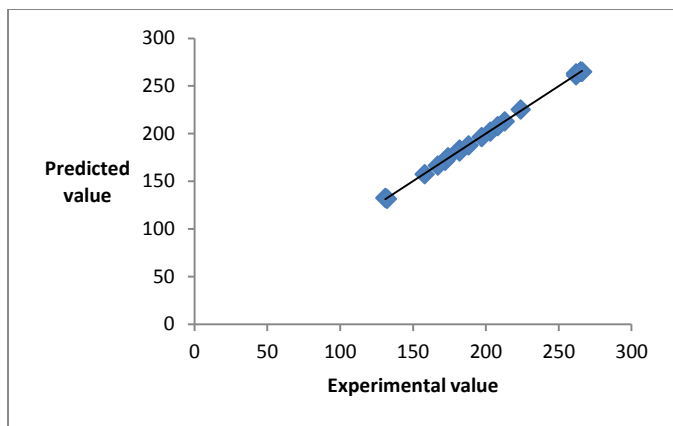


Fig 4 Graphical representation of comparison of predicted and actual value of 8011 Al/15% SiCp composites.

Fig 4 shows the comparison between measured and predicted value 8011 Al/10SiCp composites. It was found that the predicted tensile strength were close to the experimental values. From the tables 1 maximum percentage of deviation in prediction of tensile strength for 8011 Al/ 10,%SiCp composites value is 0.8 and the minimum percentage deviation is 1.14[18,19].

Table 1 Comparison between the Experimental value and predicted value of tensile strength for 8011 Al/15%SiCp composites

Experimental value for tensile	Predicted value for tensile	Error
203	202.2	0.8
224	225.4	-1.4
182	183.4	-1.4
172	171.4	0.6
174	175.2	-1.2
182	181.3	0.7
213	213.02	-0.02
188	187.6	0.4
131	132.5	-1.5
132	131.5	0.5
167	166.6	0.4
158	157.4	0.6
197	196.24	0.76
208	207.7	0.3
262	261.4	0.6
265	264.79	0.21
262	263.4	-1.4
265	264.79	0.21
266	264.79	1.21
265	264.79	0.21

3.4 FRACTURE MECHANISM:

Fig.5 Shows the fracture surface of 8011 Al/15%SiCp composites at peak aged condition. The composites still maintains its ductility, as displayed by the large and deep dimples observed. It is interesting to see the precipitation of very fine particles homogeneously distributed within the matrix [14, 15].

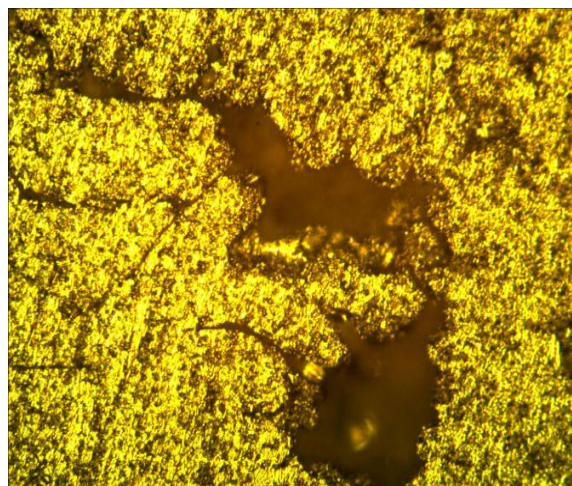


Fig.5 Fracture surface of the composite at aging time for 5 hours at 170°C.

4. CONCLUSIONS

The following conclusions could be drawn from this study:

- Response surface methodology could be used to model the age hardening process of 8011 Al alloy/SiC particulate composite.
- ANN is an excellent tool for modeling the age hardening process of 8011 Al alloy/SiCp particulate composite.
- ANN is a much better tool than RSM in the prediction of tensile values obtained from age hardening of 8011 Al alloy/SiC particulate composite.
- The comparison between measured and predicted value 8011 Al/15SiCp composites. It was found that the predicted tensile strength were close to the experimental values.

REFERENCES

[1] Badeshah, H.K.D.H., "Neural Network in Materials Science", 1999, ISI Journal International Volume 39 No. 10, pp. 969-979.

[2] Shah, I., 2002 "Modeling Mechanical Properties of Austenitic Stainless Steel", Master Theses, Cambridge University, UK.

[3] Genel, K., Kurnaz, S.C., and Drman, M., 2003 "Modeling Tribological Properties of Alumina Fiber Reinforced Zn-Aluminum Composites Using Artificial Neural Network", Journal of Materials Science & Engineering,

Volume A 363, pp. 203-210.

- [4] Sha, M.A., Edwards, K.L., 2007 "Use of Artificial Neural Network in Materials Science Based Research", *Journal of Materials Science and Design*, Volume 28, pp. 1747-1752.
- [5] Yescas, M.A., Bhadeshia, H.K.D.H., and Mackey, D.J., 2001 "Estimation of the Amount of Retained Austenite in Austempered Ductile Irons Using Neural Networks", *Materials Science and Engineering*, Volume A 311, pp. 1262-173.
- [6] Martin, W., 2003 "Application of a Backpropagation Algorithm for Feature Classification of Steel Alloys", *Automatic Microstructure Characterizations Using Machine Learning*.
- [7] Maly, M., Harck, R., and Novotny, D., 2006 "Neural Network Approach in Image Analysis of Complex System", *Vacuum*, Volume 61, pp. 233-227.
- [8] Sudhakar, K.V., and Mohammed, E.H., 2001 "Mechanical Behavior of Powder Metallurgy Steel Experimental Investigation and Artificial Neural Network Based Prediction Model JMEPEG", Volume 10, No. 1, pp. 131-160.
- [9] Ohdar, R.K., and Pasha, S., 2003 "Predication of Process Parameters of Metal Powder Preformed Forging, Using Artificial Neural Network (ANW)", *Journal of Materials Processing Technology*, Volume 132, pp. 227-234.
- [10] Jokhio, M.H., Panhwar, M.I., and Unar, M.A., 2004 "Neural Networks Application in Powder Metallurgical Process", *Proceedings of an International Conference on Frontier of Advanced Materials*, Lahore, Pakistan.
- [11] Kowalski, M., Dobranski, L.A., and Maejski, J., 2005 "Methodology of Mechanical Properties Predication for the Metallurgical Products from Engineering Steels Using Artificial Intelligence Methods", *Journal of Materials Processing Technology*, Volume 164-165, pp. 1500-1509.
- [12] Dobrzanski, L.A., and Sitech, W., 2003 "Application of Neural Networks in Steels Chemical Composition Design", *Journal of Brazilian Society Mechanical Scioty*, Volume 25, No. 2, pp. 1-7.
- [13] Jokhio, M.H., Panhwar, M.I., and Unar, M.A., 2009 "Modeling Mechanical Properties of Cast Aluminum Alloys", *Mehran University Research Journal of Engineering and Technology*, Volume 28, No. 3, pp. 367-376, Jamshoro, Pakistan.
- [14] Jokhio, M.H., 2010 "Modeling of High Strength and Wear Resistance Aluminum Alloy Based Casting Composite Materials", Ph.D. Thesis, Department of Mechanical Engineering, Mehran University of Engineering and Technology, Jamshoro, Sindh, Pakistan.
- [15] Unar, M.A., 1999 "Neural Network Modeling of Ships", Ph.D. Thesis, University of Glassgow, UK.
- [16] Talpur, M.I.H., 2003 "Intelligent Control Using Neural Network", M.E. Thesis, Mehran University of Engineering & Technology, Jamshoro, Pakistan.
- [17] Haykin, S., 1999 "Neural Networks a Comprehensive Foundation", 2nd Edition, Prentice Hall, New Jersey.
- [18] Nwobi-Okoye CC, Umeonyiagu IE. 2013, Predicting the compressive strength of concretes made with unwashed gravel from eastern Nigeria using artificial neural networks. *Niger J Technol Res* 8(2):22e9.
- [19] Nwobi-Okoye CC, Umeonyiagu IE, Nwankwo CG, 2013, Predicting the compressive strength of concretes made with granite from eastern Nigeria using artificial neural networks. *Niger J Technol* 2013;32(1):13e21.
- [20] M.C. Kimpson, and T.E. Swoff, 1989 "Processing and Properties of MMCs Containing Discontinuous Reinforcement", *Material Science and Engineering A*, Vol.107A, pp 355-358