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Modeling and optimization for microstructural properties of Al/SiC nanocomposite by artificial neural network and genetic algorithm

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ABSTRACT

Mechanical alloying process for synthesizing of Al/SiC nanocomposite powders was modeled by artificial neural network and then optimized by genetic algorithm. The feed-forward back propagation neural network model was used for predicting of the characteristics of the nanocomposite. These characteristics were the crystallite size, and the lattice strain of Al matrix. The aim of the optimization was to specify the maximum lattice strain and the minimum crystallite size of aluminum matrix that could be acquired by adjusting the process variables. Process variables included milling time, milling speed, balls to powders weight ratio that they were given as the input of the neural network model. Both modeling and optimization achieved satisfactory performance, and the genetic algorithm system proved to be a powerful tool that can suitably optimize process parameters. A comparison was made with an already carried out work; the model showed 37.6% improvement in error percentage of the crystallite size and 18.7% improvement in error percentage of the lattice strain of aluminum matrix.

1. Introduction

Many studies have been conducted to develop the engineering materials that are stronger, stiffer, and more wear-resistant than the currently available commercial materials (Suryanarayana, 2004a). Metal matrix composites (MMCs) are known as materials which their properties exceed the constituent phases and also satisfy the above requirements (Nishida, 2013). Dispersion of different kinds of ceramic particles like Si_3N_4 (Arik, 2008), $A1_2O_3$ (Canakci, Varol, & Ertok, 2012), B_4C (Varol & Canakci, 2013), TiC (Kumar, Mahapatra, & Jha, 2013) and the most commonly used particle SiC (Zafarani, Hassani, & Bagherpour, 2014) in aluminum (Al) matrix is a regular way for preparation of Al-based composites. Considering conventional Al-based composites, during embedding smaller reinforcing particles in the metal matrix, poor wettability, settling of reinforcements and inhomogeneous dispersion in the metal matrix are inevitable and subsequent treatment of thermo-mechanical processes are not effective to overcome these shortcomings (Lee, Yeo, Hong, Yoon, & Na, 2001). It has been showed that reinforcing Al matrix with much smaller particles, submicron or nano-sized range, is one of the key factor in producing of high-performance nanocomposites with improved mechanical properties (Ahamed & Senthilkumar, 2010).

Although a number of processing techniques have been developed to produce metal matrix nanocomposites (MMNCs) (Rohatgi & Schultz, 2007), mechanical alloying (MA) has been frequently used in synthesizing of these kinds of materials due to its relative ease of the process in addition to its low processing costs and fitness for fabricating nanocomposites in a large scale (El-Eskandarany, 2001). In the MA process, different kinds of brittle and ductile powders deform, weld and re-weld by a high energy ball mill in atomic level (Suryanarayana, 2004a). It is proved that the MA is one of the most economical method for synthesizing of Al-MMNCs (Canakci, Varol, & Nazik, 2012; Ruiz-Navas, Fogagnolo, Velasco, Ruiz-Prieto, & Froyen, 2006). The MA process can eliminate the segregation and agglomeration of the reinforcement particles and also, it conduces to better distribution homogeneity of the reinforcement particles into the Al (Fogagnolo, Velasco, Robert, & Torralba, 2003). Since MA process is an intricate process, it is important to take the optimal milling parameters into account in order to produce high quality productions. The MA process has many parameters that affect the final productions. The parameters are including: type of mill, milling atmosphere, milling container, extent of filling the vial, ball to powder weight ratio, milling speed, ball size, milling time, process control agent, powder size distribution, and ductility of the initial powders. These parameters influence milling stages and quality of final powders in different ways (Suryanarayana, 2004b).

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Computational intelligence and statistical techniques, such as artificial neural networks (ANN) (Canakci, Ozsahin, & Varol, 2012), genetic algorithms (GA) (Sinha, Sikdar (Dey), Chattopadhyay, & Datta, 2013) and Taguchi method (Canakci, Erdemir, Varol, & Patir, 2013a) have been earned wide applications in numerous materials engineering optimization problems. Owing to ANNs capability in simulations of the correlations that are hard to be depicted by physical models, specially the MA process, the ANN models are one of the most powerful modeling tools in this area (Canakci, Varol, & Ozsahin, 2013b). For example, an ANN model was developed to predict the effect of volume fraction, compact pressure and milling time on green density, sintered density, and hardness of Al–Al_2O_3 MMCs (Canakci, Varol, & Ozsahin, 2013c). Also, ANN model was used for the prediction of density, hardness and tensile strength of Al2024–B_4C produced by MA (Varol, Canakci, & Ozsahin, 2013).

Investigations have been shown that the microstructure of the martials such as nanocomposite could be better controlled by processing them under the far from the equilibrium conditions (Suryanarayana, 2004a). In last study (Dashtbayazi, 2012), a modeling and optimizing task using ANN as a model, and gradient descent and pattern search as optimization methods, which has been established in order to predict and optimize the ball milling process parameters for synthesizing of the nanocrystalline composite Al-8vol%SiC nanocomposite powders. The aim of this study is to specify the maximum lattice strain and the minimum crystallite size of Al matrix which could be acquired by adjusting some MA process parameters. For this purposes, the MA process is applied for producing of Al/SiC nanocomposite. The MA process variables consider milling time, milling speed, balls to powders weight ratio given as the input of the neural network model and they have straight influence on the fabricated nanocomposite bulk. Then, feed-forward back propagation neural network is used for modeling of the MA process. Next, the GA is applied to optimize the process variables for achieving the maximum lattice strain and the minimum crystallite size of Al matrix.

Table 1
Selected parameters of the mechanical alloying process.

Parameter	Symbol	Dimension
Milling time	T	minute
Milling speed	V	rpm
Ball diameter	D	mm
Balls weight	P_1	gram
Powder weight	P_2	gram
PCA weight	P_3	gram

2. ANN modeling procedure

ANN is a network containing of layers of neurons and connections between them. Neuron is the smallest computing element of a network. Each neuron in each layer receives one input signal from all neurons of its previous layer and sends one output signal to all neurons in its next layer. The following takes place in each neuron; all input signals are multiplied by a corresponding weight factor which shows the strength of that input then added to a separate bias factor. The result goes into an activation or transfer function. The most common characteristics of applications which are solved by the ANNs are (Lee, Almond, & Harris, 1999):

1. A large database is available.
2. Existing mathematical approaches show poor capability in finding precise solution for the problem.
3. Incompleteness, noisiness or complexity of the dataset.

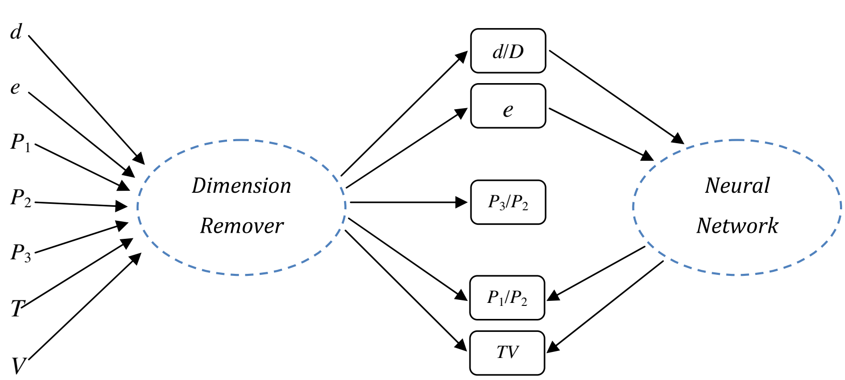

Fig. 1. Dimensional analysis and defining the inputs and the outputs of the ANN model.

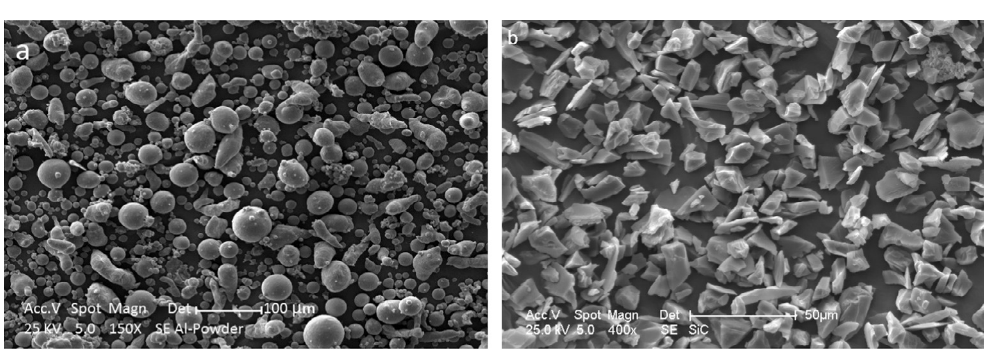

Fig. 2. SEM micrographs of elemental powders (a) Al and (b) SiC.