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Materials Science and Engineering A 466 (2007) 274–283

MATERIALS SCIENCE & ENGINEERING A

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Artificial neural network modeling of mechanical alloying process for synthesizing of metal matrix nanocomposite powders

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Received 24 December 2006; received in revised form 14 February 2007; accepted 21 February 2007

Abstract

An artificial neural network model was developed for modeling of the effects of mechanical alloying parameters including milling time, milling speed and ball to powder weight ratio on the characteristics of Al–8 vol%SiC nanocomposite powders. The crystallite size and lattice strain of the aluminum matrix were considered for modeling. This nanostructured nanocomposite powder was synthesized by utilizing planetary high energy ball mill and the required data for training were collected from the experimental results. The characteristics of the particles were determined by X-ray diffraction, scanning and transmission electron microscopy. Two types of neural network architecture, i.e. multi-layer perceptron (MLP) and radial basis function (RBF), were used. The steepest descent along with variable learning rate back-propagation algorithm known as a heuristic technique was utilized for training the MLP network. It was found that MLP network yields better results compared to RBF network, giving an acceptable mapping between the network responses and the target data with a high correlation coefficients. The response surfaces between the response variables, i.e. crystallite size, lattice strain of the aluminum matrix and the processing parameters are presented. The procedure modeling can be used for optimization of the MA process for synthesizing of nanostructured metal matrix nanocomposites.

Keywords: Artificial neural network modeling; Metal matrix nanocomposite; Mechanical alloying; Crystallite size; Lattice strain

1. Introduction

Advanced materials have been defined as those where first consideration is given to the systematic synthesis and control of microstructure of materials in order to provide a precisely tailored set of properties for demanding application [1]. High-energy mechanical milling/alloying can be used to produce several different types of advanced materials [2]. Amorphous and supersaturated alloys, nanostructured materials and nanoparticles, intermetallics and immiscible phases, coated materials and composites have been synthesized via this method [3,4]. This process involves repeated welding, fracturing, and rewelding of powder particles at the atomic level [5]. So far, understanding of the mechanisms related to the process has been achieved at phenomenological level [6]. Since mechanical alloying is a stochastic process which involves a number of both dependent and interdependent variables, the kinetics of the process is very complex. Hence, quantification and modeling of the high-energy milling process is complicated. Nevertheless, in order to develop this powerful method into mainstream industrial scale materials processing route, it is inevitable to master the art of controlling, optimizing and predicting the process by modeling.

Modeling of mechanical alloying as an intricate process has been performed by many researchers [7]. The first work in the modeling of mechanical alloying was performed by Benjamin and Volin [8] for production of a Cr–Fe alloy. They have shown that refinement of the structure is approximately a logarithmic function of time and depends on the mechanical energy input and work hardening of the material being processed. In followings, many works have been performed for physical modeling of the process including (a) phenomenological models such as mechanistic [9–13] and thermodynamic models [14], (b) microstructural models such as kinetic [15,16] and atomistic models [17], and (c) milling maps models [18,19]. Although these models yield valuable results for some aspects of mechanical alloying process, but owing to the number of influencing parameters and the inherent complex nature of the

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doi:10.1016/j.msea.2007.02.075

models as well as the need to accurate input data and the given assumptions, they cannot easy to be implemented and applied to entire path of the process variables. Additionally, lack of sufficient knowledge about the deformation behavior of materials at high impact velocities and frequencies, the outcomes are in the order of magnitude prediction and the general trends [3].

The use of artificial neural network (ANN) which is one of the most powerful modeling techniques in conjunction with the statistical approach seems quite suitable for the prediction of the mechanical alloying outputs. Over recent years the interest in the ANN modeling in different fields of materials science has been increased [20,21]. The advantages of ANN modeling are reduction of time and cost in all the required experimental activities. An ANN is essentially made up of the interconnection of simple computational elements known as neurons or nodes [22]. Any neuron in an ANN is a processing unit that can perform mathematical computations in parallel with other neurons. Arranging a number of these units in a parallel massive structure enables them to perform high computations in a short time, hence learning and memorizing the data.

Recently, synthesizing of nanostructured metal matrix nanocomposites by mechanical alloying process has been attained great interest [23–27]. Since numbers of processing parameters are involved in mechanical alloying, processing of these composites urges modeling efforts. In the present work, ANN modeling of the mechanical alloying process was performed as an example for nanostructured Al–8 vol%SiC nanocomposite. The viability of the ANN model was assessed using the experimental results. The response surfaces and contour plots of the process parameters including milling time, milling speed, and ball to powder weight ratio were established.

2. Modeling procedure

Many ANN architectures have been proposed for process modeling. The most commonly used models are the feed-forward neural networks such as MLP and RBF [28–32]. In the present work, both networks were utilized for modeling. The outcomes of the two models were compared and the suitable network was selected. In followings, the procedure for designing the neural network model is described.

2.1. Collecting the experimental data

The development of ANN models significantly depends on the experimental results. The empirical design and full size experimental testing for data acquisition for ANN modeling of mechanical alloying is either impossible or prohibitively expensive. Since numbers of parameters are involved, it is imperative to specify the most important variables. In the present work, milling time, milling speed, ball diameter, ball to powder weight ratio, and the amount of process control agent have been considered as the prime processing parameters. The characteristics of the interest are crystallite size and lattice strain of the aluminum matrix which is directly influence the structure and properties

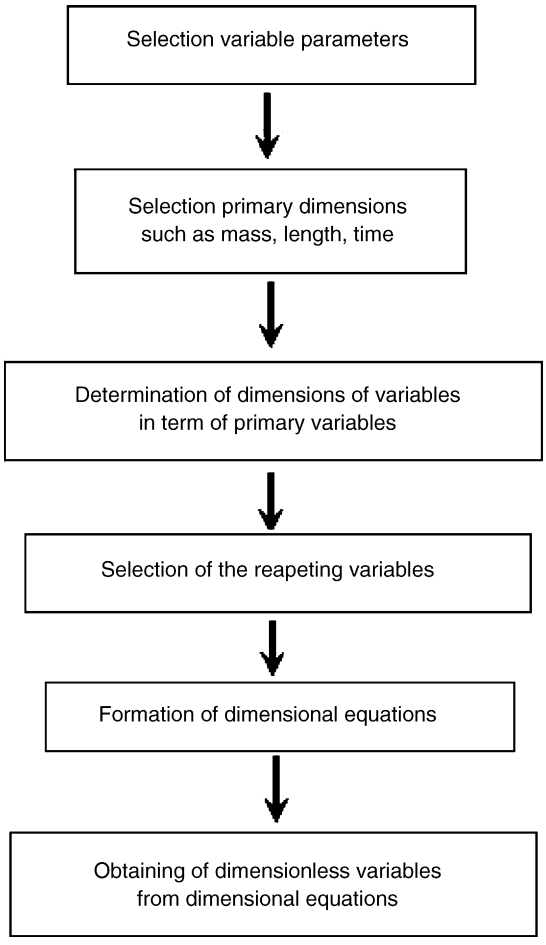

Fig. 1. Flowchart of dimensional analysis procedure.

of the fabricated nanocomposite. Therefore, it can be written:

$$(d, e) = f(t, v, D, P_1, P_2, P_3) \quad (1)$$

where d is the crystallite size of the aluminum matrix, e the lattice strain of the aluminum matrix, t the milling time, v the milling speed, D the ball diameter, P_1 the ball weight, P_2 the powder weight, and P_3 is the amount of the process control agent. Buckingham P_i theorem [33] was used to determine dimensionless parameters by dimensional analysis method. This is important because it reduces the number and complexity of the experimental variables which affects a given physical phenomenon. Fig. 1 shows flowchart of the dimensional analysis procedure used. Based on the given processing parameters (Eq. (1)) and the primary dimensions (mass, length and time), dimensionless variables were determined. The obtained dimensionless parameters are reported in Table 1. Accordingly, the equation between the dimensionless parameters can be expressed as:

$$\left(\frac{d}{D} \text{ and } e\right) = f\left(\frac{P_1}{P_2}, \frac{P_3}{P_2}, tv\right) \quad (2)$$

d/D is the dimensionless parameter, P_1/P_2 the ball to powder weight ratio, P_3/P_2 the weight fraction of process control agent in the powder, and tv is the other dimensionless parameter.