MODELING THE DRILLING PROCESS OF SOME AL-MG-CU ALLOYS AND AL-MG-CU/SIC COMPOSITES USING ARTIFICIAL NEURAL NETWORK

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Abstract: Machining of metal matrix composites (MMC's) is very important process and has been a major problem that attracts many researchers to study of characteristics of MMC's during machining process like turning, milling and drilling. This paper concerns with the potential of using feed forward backpropagation neural network in prediction of torque and thrust force during dry drilling of aluminum-copper/silicon carbide composites produced by stir casting method. The effect of the addition of copper as alloying element and silicon carbide as reinforcement particles to Al-4wt.% Mg metal matrix has been investigated by using artificial neural networks. The mean absolute relative errors between experimental and predicted values from network were 2.03% for torque, and 3.46% for thrust force. Therefore, it is suggested that by using ANN outputs, it is possible to predict the results of cutting parameters in drilling process which will be in a good agreement with the experimental ones.

Keywords: Aluminum, Artificial Neural Network (ANN), Casting, Drilling, Metal matrix Composites (MMCs)

1 Introduction

Metal–matrix composites (MMCs) are new class of materials that consist of a non-metallic phase distributed in a metallic matrix with properties that are superior to each of the constituent used (Tosun&Muratoglu,2004).Composite materials are usually classified on the basis of the physical or chemical nature of the matrix phase, e.g., polymer matrix, metal-matrix and ceramic matrix composites.

Particulate metal matrix composites (PMMC) are cheaper in both raw materials and fabrication processes and have potential for applications requiring relatively large volume production. The relative ease of fabrication of MMCs is also another favorable factor. As they can be produced by many well known methods, such as casting, powder metallurgy, and metal spray processes (Tosun&Muratoglu,2004). All such processes are readily available for manufacturing unreinforced alloys. In addition, the use of a secondary process, such as rolling, forging, extrusion and heat treatment, can be applied only to improve properties of composites without incurring significant damage to the reinforcement (Tosun&Muratoglu,2004).

Aluminum matrix composites (AMCs) refer to a class of light weight and high performance aluminum centric material systems. The reinforcement in AMCs could be in the form of continuous/discontinuous fibers, whisker or particulates, in volume fractions ranging from a few percent to 60% [3], they are usually reinforced by Al_2O_3, SiC, and C (Tosun&Muratoglu,2004; Candan&Bilgic,2004; Wain,Thomas,Hickman,Wallbank&Teer,2005; Ramulu, Rao&Kao,2002). Properties of AMCs can be tailored to the demands of different industrial applications by suitable combinations of matrix, reinforcement and processing route. In the last few years, AMCs have been utilized in high-tech structural and functional applications including aerospace, defense, automotive, sport instruments and thermal management areas.

However, because of the poor machining properties of MMCs, drilling of such materials is considered as a challenging task for manufacturing engineers. Unlike machining of conventional materials, many problems are presented during drilling of MMCs, such as tool wear and burr(Ramulu,Rao&Kao,2002;Cotterell&Kelly,2002; Monaghan&Reily,1992;Kilickap,Akır,Aksoy&Inan,2005) . Cutting forces during drilling of aluminum are generally low and because aluminum is a good conductor of heat and since most aluminum alloys melt at relatively low temperatures (i.e. less than 660 °C), cutting temperatures and tool wear rates are also low (Ramulu,Rao&Kao,2002;Cotterell&Kelly,2002). When cut under proper conditions with sharp tools, aluminum alloys acquire fine finishes through turning, drilling and milling, minimizing the necessity for grinding and polishing operations. Aluminum is commonly machined with high speed steel, diamond and carbide tooling; silicon nitride based ceramic tools are generally not used with aluminum because of the high solubility of silicon in aluminum (Cotterell&Kelly,2002). The major machinability concerned with aluminum alloys includes tool life, chip characteristics, chip disposal and surface finish (Cotterell&Kelly,2002).

The final surface finish expressed as surface roughness, Ra, during the machining of Al/SiC MMC's is much lower than that obtained during the machining of the matrix alloy alone(Tosun&Muratoglu,2004; Monaghan&Reily,1992;Kilickap,Akır,Aksoy&Inan,2005). Monaghan & Reily(1992) attributed the improved surface finish to the burnishing or honing effect produced by the action of small SiC particles trapped between the flank face of tool and the workpiece surface.

The use of artificial neural networks (ANNs) represents a new methodology in many different applications of composite materials including prediction of mechanical properties of aluminum based materials (Durmus,Ozkaya&Meric,2006;Altinkok&Koker,2005;Altinkok&Koker,2006;Zhang,Friedrich&Velten,2002;Gansen,Raghukandan,Kathikeyan&Pai,2005;Lee,Almond&Harris,1999)It is a promising field of research in predicting experimental trends and has become increasingly popular in the last few years as they can often solve problems much faster compared to other approaches with the additional ability to learn from small experimental data. Forouzan and Akbarzadeh (2006) used ANN in prediction the effect of thermo-mechanical parameters on mechanical properties of aluminum alloy AA3004. They found that well-trained ANN models provide fast, accurate and consistent results, making them superior to all other techniques. Lin,Bharracharyya&Kecman (2003) used ANN and multiple regression methods in analyzing machining parameters of aluminum alloy reinforced with silicon carbide particles with attention on tool wear. They found that ANN has ability to predict tool wear accurately from feed force.Genel, Kurnaz&Durman (2003) used multiple-layer feed-forward artificial neural network (ANN) modeling for tribological behavior of short alumina fiber reinforced zinc–aluminum composites. The specific wear rate and coefficient of friction obtained from a series of the wear tests were used in the formation of training sets of ANN (Genel,Kurnaz&Durman,2003). They found that ANN is an excellent prediction technique for both parameters if it is well trained.

2 EXPERIMENTAL SETUP AND PROCEDURE

2.1 Materials

The test materials studied in this work were a mixture of aluminum (commercial grade Al, ~99% purity) and copper granules with an average particle size of 0.425 mm and ~97% purity as a matrix and silicon carbide as reinforcement particles. About 1000 g of commercial grade Al ingots and different weight percentages of copper powder (0, 1, 2, 3, 4, and 5 wt.%) was taken to prepare the base metal matrix by casting method. Specific quantities of silicon carbide powder with an average particle size of 75µm and purity exceeds 99.5% of 5 and 10 vol.% were added to the matrix alloy. Finally, magnesium (~99% purity ingots) added in small quantities (fixed weight percentage 4wt.%) in the final stage to promote wettability between metal matrix and reinforcement particles (Candan&Bilgic,2004; Hassan,Tashtoush&Alkhalil,2007)

2.2 Processing

The synthesis of the particulate metal matrix composites used in the present study was carried out by the stir casting method (compocasting method). Aluminum ingots and copper granules melted together at 850 °C. The amount of SiC powder pre-oxidized at 900°C for about 30 minutes to form a layer of SiO_2 on their surface in order to improve their wettability with molten aluminum(Maghanaki,Lajevardi&Akhlagi,2004; Tekman, Ozdemir, Cocen & Onel,2003). were incorporated into the melt. Mg added to the melt in the final stage prior to pouring task to enhance the wettability between metal matrix and reinforcement particles. The pouring temperature was maintained at 580-600 °C in semisolid state. Then the mould was left in air to cool down to room temperature. Finally the obtained cast bars turned to small specimens of 25 mm diameter and 40 mm in length to be used in the drilling experiments.

2.3 Drilling Test

There are many types of drills but the simplest and most often used is the twist drill. This drill is simple and cheap to produce but its cutting geometry is complicated (Wyatt&Trmal,2006). The drilling test was carried out on a vertical machining center (Q&S Drillmaster, England). A general purpose 8.5 mm diameter high speed steel (HSS) twist drills (U.fA Germany) were utilized in the drilling process. The test was carried out under predetermined machining parameters with cutting speed of 300 rpm and feed rate of 0.229 mm/rev without using any lubricants.

The drilling torque and thrust force were measured with a multi-component dynamometer (TeLC BKM2000, Germany). The dynamometer signals were then processed to make them suitable for computer capture. This was achieved via charge amplifiers and an analog to digital (A/D) converter, then to the computer. The surface finish of each drilled hole was measured using Taylor-Hobson (Surtronic 3P) type instrument. Surface roughness readings were taken at least at three positions spaced at 120° intervals around the hole circumference and approximately mid-way down the depth of the hole and the averaged values were used in the training of the ANN. Quanta 200 Digital scanning electron microscopy (SEM) was used to analyze the quality of drilled holes in some investigated specimens.

3 MODELING WITH NEURAL NETWORKS

Artificial neural networks (ANN) are considered as artificial intelligence modeling techniques. They have highly interconnected structure similar to brain cells of human neural networks and consist of large number of simple processing elements called neurons, which are arranged in different layers in the network. Each network consists of an input layer, an output layer and one or more hidden layers. One of the well-known advantages of ANN is that the ANN has the ability to learn from the sample set, which is called training set, in a supervised or unsupervised learning process. Once the architecture of network is defined, then through learning process, weights are calculated so as to present the desire output (Rogier&Geatz,2003; Negnevitsky,2005)

3.1 Data Set and Processing

The input to individual ANN nodes must be numerical value and fall in the closed interval [0, 1]. Because of this conversion method the normalization technique was used in the proposed ANN according to the following formula:

$$\text{Normalized value} = \frac{\text{input value - minimum value}}{\text{maximum value - minimum value}} \tag{1}$$

Output values resulted from ANN also in the range [0, 1] and converted to their equivalent values based on reverse method of normalization technique.

3.2 Learning rules and validation

Neural networks are adaptive statistical devices. This means that they can change the values of their parameters (i.e., the weights) as a function of their performance. These changes are made according to learning rules which can be characterized as supervised (when a desired output is known and used to compute an error signal) or unsupervised (when no such error signal is used). Sigmoid function is the most common activation function in ANN because it combines nearly linear behavior, curvilinear behavior, and nearly constant behavior, depending on the value of the input [22-24]. The sigmoid function is sometimes called a squashing function, since it takes any real-valued input and returns an output bounded between [0, 1]; (Rogier&Geatz,2003; Negnevitsky,2005)

$$y = f(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

Back propagation neural networks represent a supervised learning method, requiring a large set of complete records, including the target variables. As each observation from the training set is processed through the network, an output value is produced from output nodes. These values are then compared to the actual values of the target variables for this training set observation and the errors (actual-output) are calculated. Normalized root mean square error value (NSE) was used to evaluate the training performance of the ANN (Abdelhay,2002):

$$NSE = \sqrt{\frac{\sum(\theta - \theta_0)^2}{\sum \theta^2}} \qquad (3)$$

Where θ can be the experimental value of torque or thrust force and θ_0 represents the predicted output value for each output node. More details about back-propagation training algorithm are included in literature(Altinkok&Koker,2005; Gansen,Raghukandan,Kathikeyan&Pai,2005;Frouzan&Akbarzadeh2006;Rogier&Geatz,2003; Negnevitsky,2005;Abdelhay,2002).

4 RESULTS AND DISCUSSION

The purpose of the present work was to determine the effect of the addition of alloying element (copper), and reinforcement particles (silicon carbide), on aluminum drilling process. The most important factors, which determine the condition of the work material that can influence the outcome of the machinability, are Lin,Bharracharyya&Kecman,2003)alloy chemistry, additions, physical and mechanical properties, morphology, size and volume fraction of the constituent phases, microstructure (grain refining and modification), porosity, and heat treatment.

4.1 ANN structure and results

The ANN was implemented using fully developed feed forward back propagation network. For the training problem at hand the following parameters were found to give good performance and rapid convergence: two input nodes; namely: Cu (wt.%) and SiC (vol.%), two hidden layers with 5 neurons and three output neurons (torque, thrust force and surface roughness). Sigmoid activation function was selected to be the transfer function between all layers. The ANN architecture is shown in Fig. 1.

A total dataset consists of 42 samples was used to train and test the network. Among them 32 samples were used in training process and 10 used in testing process. This dataset was obtained from compocasting process and considered as cast samples without any further post treatment except cleaning and cutting of the obtained bars. After many trials, learning rate and momentum are experimentally selected to be 0.65 and 0.20, respectively.

However, the main quality indicator of a neural network is its generalization ability, its ability to predict accurately the output of unseen data and this was achieved by testing data set. Absolute relative errors between experimental and predicted values from ANN were used to evaluate the performance of the proposed ANN in prediction technique. The mean absolute relative errors were: 2.03% for torque, 3.46% for thrust force, and 6.48% for surface roughness. The maximum absolute relative errors were 8.42% for torque, 12.02% for thrust force and 29.55% for surface roughness. However, the highest value of error corresponds to surface roughness could be processed as outlier point which appeared due to large variation as a result of drilling process and/or surface finish testing due to nature of aluminum based surfaces which consider as ductile material. This level of error is satisfactory and smaller than errors that normally arise due to experimental variation and instrumentation accuracy.

Fig. 2 shows the comparison between experimental torque, thrust force and surface roughness values and corresponding ANN outputs for Al-4wt.%Mg-Cu alloys. While Fig. 3 shows the comparison between experimental torque, thrust force and surface roughness values and corresponding ANN outputs for Al- 4 wt.%Mg-SiC composites. The columns represent measured values with ±10% error interval and continuous line represents ANN output. The ANN outputs seem to be in a good agreement with experimental values.

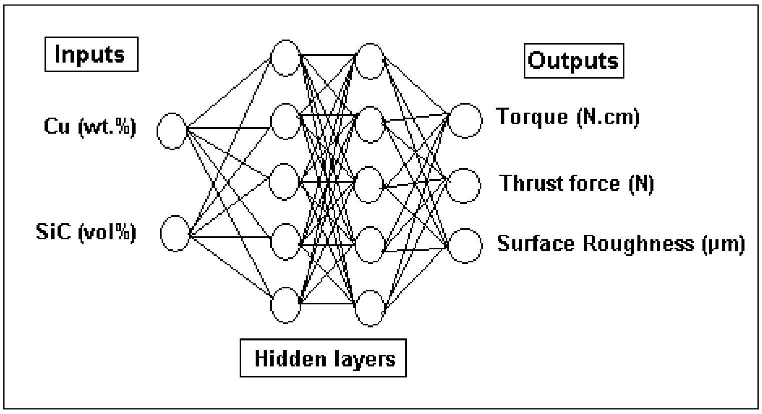

Fig. 1: The ANN architecture

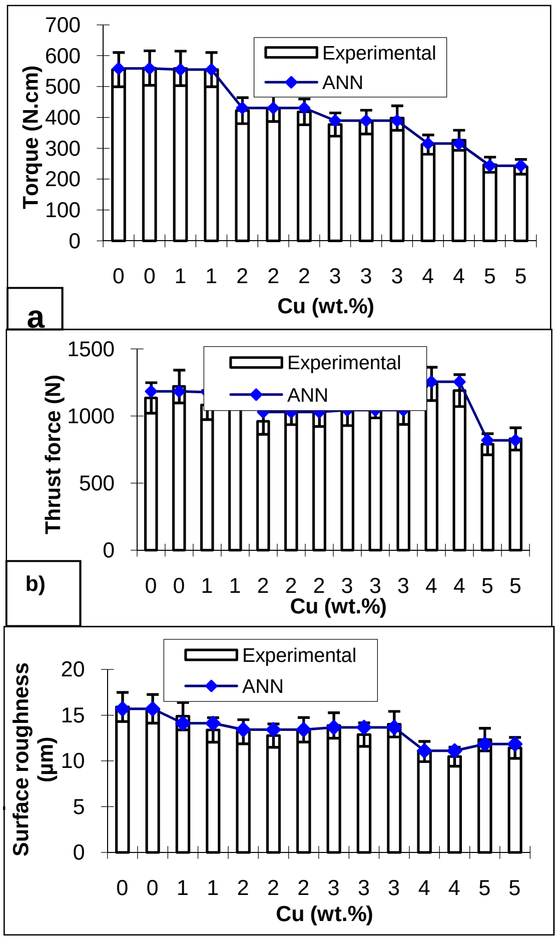

Fig. 2: Experimental values vs. predicted values for: **a)** torque, **b)** thrust force; and **c)** surface roughness with different Cu (wt.%).

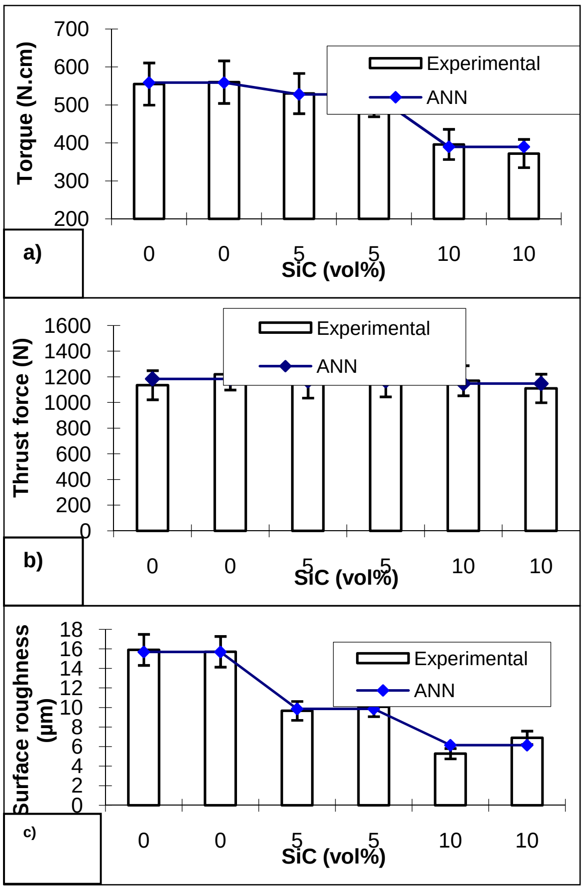

Fig.3: Experimental values vs. predicted values for: **a)** torque, **b)** thrust force; and **c)** surface roughness with different SiC (vol.%).

4.2 Effect of copper and silicon carbide addition on the drilling of aluminum

Hardness is one of the most important metallurgical parameters that can control the material machinability. In fact, aluminum alloys differ from many other metals in that the machinability of aluminum generally improves as the hardness increases. Most automotive machine shops agree that a minimum hardness of 80 Brinell is desirable (Tash, Samuel, Mucciardi&Doty, 2006). Copper and magnesium increase alloy hardness, improve the machined surface finish, and decrease the tendency of the alloy to build up on a cutting tool edge. Magnesium hardens the alloy matrix and, by doing so, reduces the friction coefficient between tool and workpiece which, in turn, results in shorter and tighter chips, and thus provides a better surface finish (Negnevitsky, 2003, Zhang, Friedrich & Velten, 2002). In the drilling results, it was also found that a lower copper content resulted in higher cutting forces (both torque and thrust force) (Zhang, Friedrich & Velten 2002). Fig. 2 shows the effect of Cu (wt.%) on the resulted torque, thrust force, and surface roughness of Al-based alloys, respectively. It is obvious that both torque and thrust force were lowered when the amount of copper was increased in the Al-4wt.%Mg matrix alloy. Also, a small addition of Mg improves the alloy machinability, lowering the cutting force and torque Lin,Bharracharyya&Kecman,2003;Tash,Mucciardi,Samuel,Valtierra&Doty,2006)

Fig. 3 shows the experimental versus predicted values of different Al/SiC composites. The general trend of machinability which can be drawn from these figures can be stated as: when the amount of SiC increases in the metal matrix, the resulted machinability is improved (mainly by lowering torque) of Al-4wt.%Mg alloy. This may be attributed to the smearing of the softer Al- 4 wt.%Mg metal matrix to the cutting tool compared to the harder matrix containing SiC particles. This is valid for lower volume fractions of reinforcement particles; however, higher volume percentages of silicon carbide will also result in higher cutting forces compared to the matrix alone due to the presence of harder ceramic particles. Improvement in the surface finish was observed due to the presence of SiC particles as shown in Fig. 6c. Tosun and Muratoglu(2004) studied the drilling process of Al/17 vol.%SiC using different cutting tools and drilling parameters. They found that as the speed and/or feed rate increased the thickness of the matrix layer increased. As the feed rate increased, the cutting temperature increased and this may cause weakening of the binding between the matrix and the SiC_P, thus the matrix softens, and motion of SiC occurred easily, and also the chips tend to be segmented easily with ductile tearing Tosun &Muratoglu,2004). The combined effect of increasing copper and silicon carbide amounts tends to improve the drilling of Al-Cu/SiC composites (lower values of torque and thrust force) compared to Al- 4 wt.%Mg alloy.

5 CONCLUSIONS

The aim of the present work was to illustrate the application of artificial neural network as prediction technique to estimate torque and thrust force as well as surface roughness of some Al-Mg-Cu alloys and their corresponding composites reinforced with 5 and 10 vol% of SiC in the drilling process. The ANN gives satisfactory results when compared to the experimental measurements. The mean absolute relative errors between experimental and predicted values from network were 2.03% for torque and 3.46% for thrust force,. Therefore, by using ANN values, satisfactory results may be estimated rather than measured and hence reducing testing time and cost.

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