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Multiple regression and neural networks analyses in composites machining

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Abstract

The machining forces-tool wear relationship of an aluminium metal matrix composite has been studied in this paper using multiple regression analysis (MRA) and generalised radial basis function (GRBF) neural network. The results show that using the force-wear equation derived from MRA is a fairly accurate way of predicting the attainment of prescribed tool wear. However, the use of a neural network analysis can further improve the accuracy of the tool wear prediction particularly when the functional dependency is nonlinear. It is evident that the relationship derived from the feed force data is more accurate than that derived from the cutting force.

Keywords: A. Metal-matrix composites; B. Wear; C. Statistics; Neural networks

1. Introduction

Increasing quantities of metal matrix composites (MMCs) are being used to replace conventional materials in many applications, especially in the automobile and recreational industries where the performance requirements are getting more demanding. Among the wide diversity of MMCs, the most popular types of MMCs are aluminium alloys reinforced with ceramic particles. These low cost composites provide higher strength, stiffness and fatigue resistance [1,2], with a minimal increase in density over the base alloy. The superior mechanical properties achieved by the reinforcements in MMCs, on the other hand, make them hard to be machined to a required shape. Therefore, only polycrystalline diamond (PCD) tools are often found to be suitable for machining these MMCs for a reasonable length of cutting time [3–5].

Due to the relatively high cost of PCD tools, they need to be changed in time for resharpening to maximise the total useful tool life. In order to decide the right time for tool change, continuous monitoring of the tool wear needs to be done during the machining operation. The commonly used experimental method of examining the tool wear using microscopy involves interruptions in the cutting process. However, an indirect way of monitoring the tool wear, in which a measurable output might be used to indicate the extent of tool wear without interrupting the machining process, would be more suitable for practical applications. Such outputs may be the cutting and feed forces that are dependent on tool wear [6,7].

From previous research [3–7], it is now well known that the primary wear mechanism in machining particulate reinforced MMC is abrasion by the reinforcing particles on the flank surface of the tool. Figs. 1 and 2 show the curves of the typical tool wear growth and changes of machining forces for machining the DURALCAN® (registered trademark of Alcan Aluminium Ltd.) MMC (SiC particulate reinforced aluminium metal matrix composite material, A359/SiC/20p) in three different cutting conditions. It is clear that the tool wear and the two machining forces increase steadily with time following the similar trends. The general Taylor's equation showing the relationship between tool wear and cutting conditions has been derived in an earlier paper

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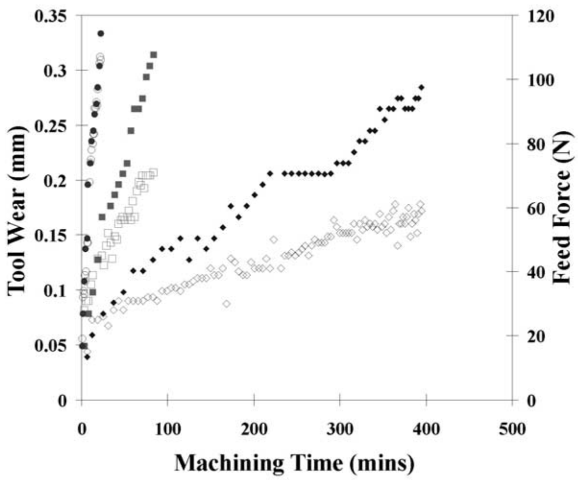
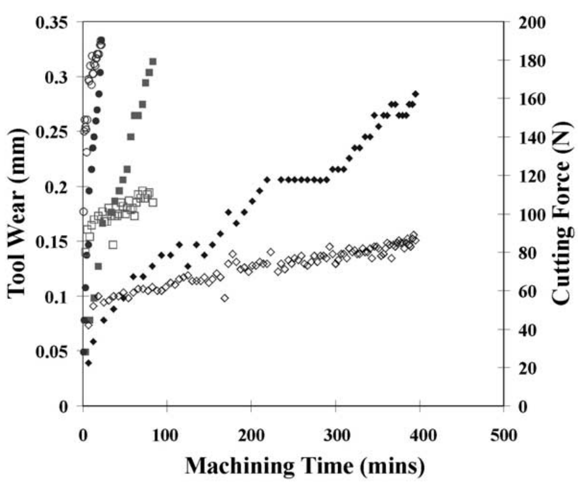


Cutting Conditions	300 m/min, 0.1 mm/rev	500 m/min, 0.2 mm/rev	700 m/min, 0.4 mm/rev
Wear	◆	■	●
Force	◇	□	○

Fig. 1. The comparison of curves of the typical tool wear growth and changes of feed force in three different cutting conditions.



Cutting Conditions	300 m/min, 0.1 mm/rev	500 m/min, 0.2 mm/rev	700 m/min, 0.4 mm/rev
Wear	◆	■	●
Force	◇	□	○

Fig. 2. The comparison of curves of the typical tool wear growth and changes of cutting force in three different cutting conditions.

[7], which may be used to predict the tool life when machining the SiC reinforced aluminium composites. The similar trends of change in the tool wear and machining forces suggest that the measurement of machining forces during the machining process may be used as an indirect way of monitoring tool wear if a proper relationship can be found between these two parameters.

In this paper the relationship between the tool wear and the machining forces during machining DURALCAN material has been established using both multiple regression and artificial neural network analyses. A general equation involving machining conditions (cutting speed and feed rate), machining force (either feed or/and cutting) and tool wear has been derived from multiple regression analysis (MRA), and the same data have been analysed using generalised radial basis function neural network. The accuracy of predicting tool wear using both methods will also be compared.

2. Background of neural network

The use of neural networks (NNs) represents a new methodology in many different applications including tool condition monitoring for machining of traditional enginering materials [8–22]. 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. Generally, a neural network means a network of many simple processors (“units”) operating in parallel, each possibly having a small amount of local memory. The units are connected by communication channels (“connections”) which usually carry numeric (as opposed to symbolic) data, encoded by one of various ways [23]. One of the best known examples of a biological neural network is the human brain. It has the most complex and powerful structure which, by learning and training, controls human behaviour toward responding any problem encountered in every-day life. As for the artificial neural networks (ANN), they have been developed to try to emulate this biological network for the purpose of learning the solution to a physical problem from a given set of examples.

Among the many neural networks that have been developed, the most popular neural networks are known respectively as the multilayer perceptron (MLP) and the generalised radial basis function (GRBF) network [8,9]. These networks currently form the basis for the majority of practical applications. In this paper, however, the GRBF network is chosen, since it provides several advantages over the MLP network and has been proven successfully in different applications [9,19–22]. The GRBF network is based on the simple intuitive idea that an arbitrary function $y(\mathbf{x})$ can be approximated as the linear superposition of a set of localised basis functions $\varphi_j(\mathbf{x})$. A network diagram, as shown in Fig. 3, can represent the structure of the GRBF network. The architecture of a GRBF network consists of three layers—*input, output* and *hidden* layers. The hidden layer, situated between the input and output layer, is where the basis functions operate to intervene between the