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Monitoring of tool wear using measured machining forces and neuro-fuzzy modelling approaches during machining of GFRP composites

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ABSTRACT

The challenges of machining, particularly milling, glass fibre-reinforced polymer (GFRP) composites are their abrasiveness (which lead to excessive tool wear) and susceptible to workpiece damage when improper machining parameters are used. It is imperative that the condition of cutting tool being monitored during the machining process of GFRP composites so as to re-compensating the effect of tool wear on the machined components. Until recently, empirical data on tool wear monitoring of this material during end milling process is still limited in existing literature. Thus, this paper presents the development and evaluation of tool condition monitoring technique using measured machining force data and Adaptive Network-Based Fuzzy Inference Systems during end milling of the GFRP composites. The proposed modelling approaches employ two different data partitioning techniques in improving the predictability of machinability response. Results show that superior predictability of tool wear was observed when using feed force data for both data partitioning techniques. In particular, the ANFIS models were able to match the nonlinear relationship of tool wear and feed force highly effective compared to that of the simple power law of regression trend. This was confirmed through two statistical indices, namely r^2 and root mean square error (RMSE), performed on training as well as checking datasets.

1. Introduction

The direct contact between cutting tool, workpiece material, and the chips during machining operation imposes extreme thermal and mechanical stresses on the cutting tool. As a result, changes to the geometry, volume loss, and sharpness of the cutting tool, can occur either gradually or abruptly. These changes, which are known as tool wear, normally take place at the rates dependent upon machining conditions, workpiece material, as well as the cutting tool material or geometry. As discussed in earlier research study [1], abrasive wear on the flank face of the cutting tool has been the dominant wear mechanism that influences the tool sharpness during machining of glass fibre-reinforced polymer (GFRP) composites. On the basis of this, reduction of tool sharpness puts constraint on the dimensional accuracies and surface qualities of the composites product. Often, in-service or mechanical performance of poorly machined GFRPs degrades and under the worst circumstances, causes them rejected prior to the end applications. Similar to the case of metallic materials and their metal matrix composite counterparts, it is essential to develop accurate tool wear predictive models as monitoring its condition during machining can extend its useful life.

There exists a significant body of literature pertaining to tool condition monitoring for metal cutting processes which have been reported in the past few decades. In fact, the concept of tool condition monitoring evolved in the early 1990s. In general, the condition of the cutting tool can be determined through two possible methods, namely *direct* and *indirect* methods. Broadly speaking, Dan and Matthew [2] define them to be as: (1) direct, where the actual tool wear is measured in-situ; (2) indirect, where a parameter correlated with tool wear is measured. Direct measurement using optical devices has been extensively and effectively employed in studying the extent of tool wear as well as to understand its mechanisms. The optical measurement of tool flank wear has also been proven to be useful in estimating the tool's useful life by employing the classical Taylor's tool life equation. However, this would require interruptions of the cutting operations due to the need to remove the tool from its holder for the optical microscopy.

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This consequently demotes machining productivity due to unscheduled downtime of the cutting operation.

An indirect approach that involves the measurements of machining signals, which can be correlated to the tool wear, offers a more practical solution for industrial application. Thanks to the availability and on-going advancement of various sensors for machining tests in recent years, reliable and accurate monitoring of tool condition can be realised. Nonetheless, machining operation is known to produce harsh environment or conditions. In view of this, Dimla summarised that any machining processes can be classified as having one or more of the following characteristics [3]: (1) complex to stochastic behaviour due to in-homogeneities in the workpiece material; (2) sensitive to the process parameters or cutting conditions; and (3) nonlinear relationship between the process parameters and tool wear.

The aforesaid stochastic phenomenon makes it a challenge to achieve highly accurate and reliable tool wear prediction or condition models. As a result, empirical based model derived from experimental data or machining signals has been used and is viable enough to draw scientific conclusions about the tool condition. Such signals can come from various sources or sensors although machining forces have predominantly been used in the past research studies. This is evident in the summary of selected literature (taken from a broad spectrum of research articles) related to the tool condition monitoring [2–10]. Machining forces are considered to be the most informative for indirect tool wear monitoring or conditional signals. They can be directly correlated to the sharpness of the cutting edges (tool wear), chip geometry, and machining conditions.

Indeed, this has been reported by Ravindra et al. [9], in which the authors developed a multiple nonlinear regression analyses of tool wear using machining force signals measured from experiments during turning of cast iron with coated carbide inserts. The authors claimed that the cutting force components were found to be well correlated with the progressive wear and the tool failure, which can be an effective on-line monitoring of the tool condition. In a recent study, Jemielniak et al. [4,5] reported the tool wear monitoring using various sensors which include force dynamometer, accelerometer, and acoustic emission (AE) sensor. However, it is imperative to note that AE sensors are highly sensitive to any noise generated from the external environment. Hence, the application of AE sensors as a tool wear indicator is only deemed to be suitable as an additional sensing device in support to the main sensor or device.

Presently, among many research endeavours on tool wear prediction or condition monitoring, one can find limited numbers of published results for composite materials. The only such study was reported by Lin et al. [6] during turning of aluminium silicon carbide metal matric composites. Effort must be undertaken to extend the concept of tool condition monitoring from metal cutting process into composite machining, especially the GFRP composites, for any industrial useful applications. Notably, a timely decision on tool condition prior to the end of its useful life is inevitably crucial in reducing any detrimental effects of the worn tool on the machined surface. In spite of this, chaotic behaviour of machining response seems to impede the progress of developing a reliable tool wear predictive model for any practical use during machining of this material due to the laminated nature of the GFRP composites. Hence, this paper describes the attempt to develop and compare the performance of tool wear predictive models during machining of the GFRP composites. These predictive models have been established using the widely employed soft computing technique namely; Adaptive Network-Based Fuzzy Inference System or simply known as ANFIS.

Soft computing, as the name suggests, refers to a collection of computational techniques developed from computer science research. The major aims are to model and analyse complex, nonlinear, and imprecise phenomena that may exist in the process variables. The techniques are usually robust and capable of yielding complete, accurate, and reliable solutions. Such examples of soft computing modelling frequently employed in machining research include artificial neural network (ANN), fuzzy logic modelling, and genetic algorithms (GA). Hitherto, the soft computing technique has emerged as an alternative method to complement the statistical technique for modelling of machining processes. Successful implementations of these approaches in modelling machining processes have, indeed, been summarised in several review reports [11–16]. Some of the published results are discussed herein (particularly those related to fuzzy logic, ANFIS and ANN modelling techniques).

Gill et al. [17] have developed tool wear model based on ANFIS technique in their study of turning hot rolled annealed steel stock (C-45) with cryogenic cutting tools of different temperatures. The model combined fuzzy inference function and artificial neural network training with a set of rules in estimating the extent of tool wear. In this study, three parameters (cutting speed, cryogenic temperature and machining time) were used as input parameters and their range of values were represented using triangular membership function. Based on the selected parameters and their levels, 27 fuzzy rules were formulated. The authors asserted that the predictions well agreed with the experimental data, with correlation coefficients to be 0.994 and mean errors of 2.47%.

Despite these promising results, the authors highlighted that the predictive accuracy of the model very much depends on the appropriate training of the neural network as well as data points selections [17]. The same authors also reported the modelling of material removal rate (MRR) during stationary ultrasonic drilling of sillimanite ceramic [18]. In this study, 4 ANFIS fuzzy rules were employed to predict the MRR according to three input parameters, namely the depth, time and rate of penetration. In a different study, Palanikumar et al. [19] proposed the applications of fuzzy logic in modelling the surface roughness of CFRP composites during turning operation. The Mamdani fuzzy logic rules were constructed based on Taguchi L_{27} experimental array in which each fuzzy expression has been divided into three membership functions of 'Low', 'Medium' and 'High'. However, the authors claimed that the effectiveness of the fuzzy model is only within the range and factors implemented in their study. Hence, they suggested that the accuracy of the proposed model can be further improved by considering more variables and range of parameters.

The capability of ANN technique to be a highly accurate predictive model for surface roughness, R_a in end milling titanium alloy (Ti–6Al–4V) has been recently demonstrated by Zain et al. [20]. In this work, the authors have utilised a feedforward backpropagation algorithm with traingdx, learngdx, mean square error (MSE), logsig as the training, learning, performance and transfer functions, respectively. Despite the accuracy of the prediction model, the authors asserted that predictive capability could be improved by modifying the number of layers and nodes in the hidden layers of the ANN network structure.

In another work, Zain et al. [21] compared multiple regression analysis and ANN for prediction of minimum R_a value in machining process. Contrary to their previous results, in this study, the authors reported that regression technique has given a slightly better result when compared to ANN in predicting the minimum R_a value. In this work, the minimum R_a values from experiment, regression and ANN were 0.190 mm, 0.187 mm, and 0.188 mm respectively.