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Development of energy consumption model of abrasive machining process by a combined evolutionary computing approach

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ABSTRACT

Abrasive machining is employed for improving surface characteristics of components used in oil and gas applications. Optimization of power consumed in abrasive machining process is vital from environmental standpoint that requires the formulation of the generalized and an explicit mathematical model. In the present work, we propose to study the power consumption in abrasive machining process using a combined evolutionary computing approach based on Multi-Adaptive Regression Splines (MARS) and Genetic Programming (GP) techniques. Sensitivity and parametric analysis have also been conducted to capture the dynamics of process by unveiling dominant input variables and hidden non-linear relationships. It is concluded that selection of optimal machining time and abrasive is necessary for achieving better environmental performance of abrasive machining process.

1. Introduction

Abrasive machining is widely used in aerospace manufacturing industries for achieving the desired surface finish of engineering components. Since power is an essential and expensive component for driving the machining operations, the saving of energy would result in higher environmental performance and productivity. Some studies conducted by peer researchers [1–3] reveal that more focus has been paid in optimizing the metal cutting operations based on cost and productivity. Recently, few studies are conducted that address the implications of conducting machining operations on its environmental performance [4,5]. However, to the best of authors' knowledge, any study that discusses the implications of abrasive machining of components on the environmental aspect is hardly noticed.

The mechanics of abrasive machining process with respect to input process variables has been well investigated in literature studies. Nouhi et al. [6] presented a novel technique using shadow masks which can be moved over the surface of the machined component. This allowed in direct measurement of features from the surface. Çelik et al. [7] investigated the effects of cutting parameters and geometrical features of novel α/β-SiAlON drilling tools on the cutting forces and the peel-up delamination of the machined holes. They observed that the point angle and chisel edge length of the novel SiAlON drilling tools are the main parameters that affect the maximum thrust force and delamination during drilling. Hadavi et al. [8] presented a novel model capable of predicting the instantaneous particle orientation and velocity within and

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downstream of the nozzle. It was evident from their results that formulation of mathematical models may have important implications for optimizing solid particle erosion tests and in abrasive jet machining applications. Wu et al. [9] proposed a new ultra-precision magnetic abrasive finishing process using low frequency alternating magnetic field. They demonstrated that the surface roughness of SUS304 stainless steel plate was improved from 240.24 nm to 4.38 nm by their novel approach. Saidi et al. determined the factors governing the dust emission during granite polishing in order to reduce the risk of exposition while producing quality parts. They performed experiments on a vertical CNC machining center using an adaptable tool holder which controlled the contact pressure during the tests. The studies established that the polishing tool grit size governs not only the granite surface finish but also the fine particle emission and the chip removal mechanism.

Some finite element modeling (FEM) studies have also been dedicated to understand the mechanics of abrasive machining process. Barletta et al. [10] modeled the material removal during fluidized bed of ductile metals by combining the theory of localization of plastic deformation during abrasive–workpiece impacts with an energy absorption approach. Hence, analytical modeling of abrasive machining process is also gaining popularity due to their cost effectiveness and time savings factor. However, the formulation of these models requires a thorough knowledge on the functionality and the configuration of the abrasive machining system.

In addition to finite element modeling of abrasive machining process, standardized Computational Intelligence (CI) techniques such as Genetic Programming (GP), Multi-Adaptive Regression Splines (MARS), and Artificial Neural Networks (ANN) can be used as an alternative method for modeling complex physical non-linear systems such as abrasive machining process. GP offers the advantage of fast and cost-effective explicit formulation of a mathematical model based on multiple variables with no existing analytical models. However, application of a standardized GP method may not perform satisfactory on the test data. Poor performance of the model on the test data implies its poor generalization ability and results in false information of the process in uncertain input process conditions. In addition, the data samples are costly to obtain and therefore the experts are looking for the high fidelity models that can predict the process behavior in extreme conditions. It is also well learned from the literature [11,12] that by integrating the characteristics of the two or more methods, the generalization ability of the given method can be improved. This forms the motivation to introduce a new hybrid concept of parallel mechanism based on two potential CI methods of GP and MARS.

In the present work, the combined MARS–GP approach is proposed, which comprises of MARS model and GP error model in parallel. The error model is formulated using the GP approach based on evaluating the errors of the predictions of the MARS model. During the training of GP, the four process parameters, viz. component, machine acceleration, abrasive grade and machining time. Based on these inputs, a computational model for power consumption is formulated which needs to be optimized for improving the environmental sustainability. The MARS–GP model performance is further compared to that of standardized MARS model. The parametric and sensitivity analysis is further conducted to validate the robustness of the proposed approach.

2. Experimental study of abrasive machining process

The data for model development in our study is obtaining by conducting comprehensive experiments on abrasive machining process. Three types of workpiece components were tested in our study, viz. steel, nickel and titanium. The workpiece component is taken into consideration in the mathematical model by the component density. In addition, the abrasive grade is defined by the abrasive grain size in our study (hereafter referred to as "abrasive"). At the beginning, we loaded the component in the abrasive machine and the abrasive machining for performed for various machine velocities and by changing the abrasive grade systematically. A load cell is deployed to measure the cutting force and the power consumption is computed in our study as the product of cutting force with the machining velocity. The abrasive machining process is then repeated for different components and the output data is then generated for different combinations of input machine factors.

We consider four system input parameters based on the above mentioned parameters, viz. component (x_1), machine velocity (x_2), abrasive (x_3) and machining time (x_4). The measured output parameter of the computational model is power consumed (y_1) during the machining process. The descriptive statistics of the data sets obtained from our experiment is shown in Table 1. It should be noted that the learning capability of the algorithm depends on the selection of training and testing data, which is obtained by using Kennard-and-Stone algorithm. In this study, 141 samples are used as training data sets and the remaining forms the testing data. The data is then fed into paradigm of MARS–GP cluster for the training of models.

3. Proposed computational approach

3.1. Combine MARS–GP approach

In order to understand the notion of MARS–GP approach, firstly each of them is discussed as follows.

Genetic Programming (GP) generates the models automatically based on the given data using the Darwinian principle of "Survival of the fittest" [13]. Working principle of GP is same as GA but the only difference between them is that GA evolves solutions represented by strings (binary or real number) of fixed length whereas GP generates solutions represented by tree structures of varying sizes. GP algorithm starts by generating the models randomly. The numbers of models generated are represented by the population size. The models are formed by combining the elements randomly from the functional and terminal set. A