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Prediction of stable cutting depths in turning operation using soft computing methods

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ABSTRACT

This article suggests soft computing methods to predict stable cutting depths in turning operations without chatter vibrations. Chatter vibrations cause poor surface finish. Therefore, preventing these vibrations is an important area of research. Predicting stable cutting depths is vital to determine the stable cutting region. In this study, a set of cutting experiments has been used and the stable cutting depths are predicted as a function of cutting, modal and tool-working material parameters. Regression analyses, artificial neural networks (ANN) decision trees and heuristic optimization models are used to develop the generalization models. The purpose of the models is to estimate stable cutting depths with minimum error. ANN produces better results compared to the other models. This study helps operators and engineers to perform turning operations in an appropriate cutting region without chatter vibrations. It also helps to take precautions against chatter.

1. Introduction

During machining high-precision mechanical parts, the static and dynamic behaviour of the machining system is a critical factor that significantly influences the surface quality. Generally, vibrations in the machining systems can be divided into the sum of the free, forced and self-excited vibrations. Free and forced vibrations can be easily detected and suppressed and their effect is low. In contrast, chatter vibrations negatively affect surface quality of the parts. Additionally, they can lead to abnormal tool wear and tool breakage. Therefore, preventing chatter vibrations is essential. The main reason for chatter in turning is the regenerative effect, which is a sum of the instantaneous tool-workpiece relative vibration [1]. Regenerative chatter is effective at medium-high cutting speeds. In contrast, at low cutting speeds, the rubbing of the tool major flank against the machined surface, known as process damping, is likely to reduce chatter vibrations [2].

Metal machining is often accompanied by severe relative motion between the tool and the workpiece, which is referred to as chatter vibration. Turning operations are currently restricted by complicated chatter problems. These chatter problems lead to a severe deterioration of the machined surface, increase the rate of tool wear and decrease the spindle life. The problems are challenging because the vibrations cause a reduction in the productivity rate. Chatter vibration produces insufficient surface quality, low accuracy, excessive noise, increased tool wear, increased tool damage and high costs [3].

Chatter vibration in machining is prevented by selecting stable cutting parameters. To display the combinations of the width of cut and cutting speed, stability maps can be developed to determine the stable cutting parameters. As a result, determining stable cutting depths is crucial in machining operations without chatter problem [4,5].

Research into chatter vibrations during turning process has a long history. Different analytical models were developed to predict chatter stability. Studies in the literature are classified according to the number of degrees of freedom (DOF), tool-workpiece flexibilities [6–9], tool wear and process damping [10,11]. A number of researchers used Nyquist plots and finite element analyses and carried out experiments measuring force and vibration in an attempt to estimate chatter stability [12–14]. In recent literature, Urbicain et al.'s [15] study focuses on the problem of identifying stability charts when cutting Inconel 718. The method finds the free-chatter regions in longitudinal chatter when the tool vibrates in the tangential direction. The study proposes one and two degree of freedom (DOF) dynamic model to carry out the effect of the tangential mode on chip regeneration in the regenerative plane. Tyler and Schmits [16] find an analytical solution for turning and milling stability that involves process damping effects. Comparisons between the new analytical solution, time-domain simulation, and experiments are presented. The velocity-dependent process damping model applied in the analysis depends on a single coefficient. The process damping coefficient is determined experimentally via a flexure-based machining setup for a chosen tool-workpiece pair. The effects of tool wear and the cutting edge relief angle are also analyzed. Otto et al. [17] study chatter vibrations in cutting processes, and a unified method for the computation of the stability lobes for the turning, boring, drilling and milling processes in the frequency domain is provided. The method can be used for fast and reliable detection of the stability lobes. The presented analysis is appropriate for getting a deep understanding of the chatter stability, which is dependent on the parameters of the cutting process and the structure. Chen et al. [18] proposed a new dynamic cutting force model with nominal chip thickness to estimate the stability of interrupted turning, in which the dynamical cutting force is described by a function of the nominal chip thickness and the dynamical chip thickness. The stability lobes of interrupted turning are acquired via the full-discretization method and Floquet theory.

In the literature, some parameters (geometrical, material, etc.) were kept constant, and orthogonal cutting conditions were assumed. Therefore, analytical models were developed based on these assumptions. In some circumstances, oblique cutting conditions should be taken into account. Moreover, all cutting, geometrical and modal parameters have not been observed at the same time before. Furthermore,

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soft computing methods weren't used before to predict chatter vibrations. This study investigates all the effective cutting parameters and combines orthogonal and oblique cutting conditions at the same time. The proposed models help operators and engineers to select appropriate parameters without chatter. This study will lead to predict stable cutting depths and stability maps with different cutting parameters.

This research attempts to determine the stable cutting depths without chatter. The paper has five parts. First, it reviews the extant literature relevant to chatter stability prediction. Then, soft computing methods used in the study are explained briefly. Subsequently, experimental and computational studies are presented respectively. Next, the findings are discussed and summarized. The paper concludes with a discussion of the theoretical and practical applications and directions for further research.

2. Soft computing methods

The methods used in the study are explained briefly below.

2.1. Multiple linear regression models

Multiple linear regression models predict the best-fitting linear equation for the output values according to the input values. The multiple linear regression equation shows a straight line, which minimizes the squared differences between the estimated and real output values. This is a popular statistical technique that is used in estimations [19].

Multiple regression models are simple and provide an easily interpreted mathematical equation for predictions. This type of modelling is a long-established statistical procedure; therefore, the properties of these models should be well known. The models are also easily trained. The multiple linear equations are provided in Eq. (1). The error term is shown in Eq. (2).

$$y_i = B_0 + \sum_{i=1}^{n} B_i X_i + e_i \tag{1}$$

$$e_i = Y_{i_{actual}} - Y_{i_{predicted}} \tag{2}$$

B_0, B_i: constant terms; y_i: the dependent variable; X_i: independent variables; e_i: error term.

The determination coefficient is calculated as follows (Eq. (3)):

$$R^2 = 1 - \frac{SS_{error}}{SS_{total}} \tag{3}$$

SS_{error}, sum of squares for errors; SS_{total}, sum of squares for total.

2.2. ANN

ANN models are basic models of the operation of the nervous system. The standard units of neural networks are neurons. A neural network is a basic model that shows how the human brain processes information. This network simulates interconnected processing units. The processing units are organized in layers. A neural network is usually composed of three parts: an input layer, an output layer and hidden layers. The units are linked to different weights [19].

The network learns by examining specific records. The network generates an estimate for each record and changes the weights when an incorrect prediction occurs. This procedure is replicated, and the network improves the estimates until the stopping criteria are achieved. At first, all weights are arbitrary, and the answers are nonsensical. The network learns via training, and the responses are compared with the known results during the procedure. Information from this comparison is passed back through the network, and the network slowly alters the weights. After the training, the network can be used in future scenarios [19].

Sum function is given as follows (Eq. (4)):

$$u = \sum_{i=1}^{n} w_i x_i + b \tag{4}$$

x_i, input nodes; w_i, weights; b, bias.

Different activation functions are used in ANN. An activation function of sigmoid is shown as an example (Eq. (5)):

$$y = \frac{1}{1 + e^{-u}} \tag{5}$$

2.3. Classification & regression tree models (CART)

Decision tree models can be represented as a collection of if-then rule sets that show the information in an understandable way. The decision-tree display is helpful to understand how attributes in the data can be divided, or partitioned, into subsets relevant to the problem. The rule set display is beneficial to see how particular groups of items relate to a specific conclusion [19].

CART node is a tree-based classification and prediction technique. The technique uses recursive partitioning. The purpose is to divide the training data into subgroups with similar output data. CART begins by analyzing the input data to find the best split, measured by the decrease in an impurity index that is caused by the split. The split defines two subgroups. These subgroups consequently split into two more subgroups, till one of the stopping criteria is triggered. All splits are binary [19].

CART permits the tree to grow to a large size before pruning based on more complicated criteria. This may cause smaller trees which have better cross-validation properties. An increase in the number of terminal nodes usually decreases the risks in the training data [19].

The Gini impurity, information gain, and variance reduction are the metrics used in the model. The metrics are calculated as follows (Eq. (7) and (8)):

$$I_G(f) = \sum_{i=1}^{m} f_i (1 - f_i) \tag{7}$$

$$I_E(f) = -\sum_{i=1}^{m} f_i \cdot \log_2 f_i \tag{8}$$

f_i, the fraction of items labelled with value i in the set.

The variance reduction of node N is defined as the total reduction of the variance of the target variable x resulting from the split at this node (Eq. (9)):

$$I_v(N) = \frac{1}{|S|}\sum_{i \in S}\sum_{J \in S}\frac{1}{2}(x_i - x_j)^2 - \frac{1}{|S_t|}\sum_{i \in S}\sum_{J \in S}\frac{1}{2}(x_i - x_j)^2 + \frac{1}{|S_f|}\sum_{i \in S}\sum_{J \in S}\frac{1}{2}(x_i - x_j)^2 \tag{9}$$

S, S_t, S_f: the set of presplit sample indices.

2.4. Heuristic optimization models

Genetic, cuckoo search and particle swarm algorithms are explained below.

2.4.1. Genetic algorithm

A genetic algorithm (GA) is a heuristic algorithm using natural selection and the population genetics mechanism [20,21]. The fundamental idea of a GA is about the biological process of survival and adaptation. In the genetic algorithm method, different decision