Model of the milling process on the basis of cutting force: A Neural Network-based Approach

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Abstract: Recent developments, focused on the optimization of machining processes, through an effective cutting force control, should be complemented with a thorough monitoring of the transient response of these systems, because undesirable oscillations in cutting force are harmful to finishing quality and cutting tool integrity. The main goal of this work is to introduce a versatile neural network-based model, capable, by its on-line running, to accurately predict the cutting force, under common functioning conditions. Using this model, easily obtained from straightforward machining tests, further developments of complex adaptive controllers and monitoring systems can be carried out.

Key-words: neural networks, modeling, milling process.

1 Introduction.

Nowadays, due to the new requirements of process monitoring in milling operations, the knowledge of the cutting force pattern is invaluable for the assessment of cutting tool deflection, wear, breakage, vibration, and their effects on the quality of the finished product. The cutting force model of the milling process has been extensively studied both analytically and empirically with two well-defined objectives: the development of intelligent online tool condition monitoring systems and the design of adaptive and robust controllers in order to optimize the milling process.

Analytical models may be sound in principle but they require parameters such as dynamic stress, shear angle and friction angle which are usually not easily determined in practice. As a result, a more empirical approach for modeling a milling process has been popular and well developed. Up to date, most of the research deals with the development of force equations considering run out, cutter geometry, and other parameters. Nevertheless, a force model, which deals with more complicated machining situations and real time modification of cutting parameters, should be developed.

Among all the available identification techniques, Artificial Neural Networks (ANN) represent an outstanding approach to model complex processes due to the feasibility for hardware implementation, real-time running, and a few prior assumptions for modeling [7]. Some results show that the implementation of ANN approach can yield a more accurate process model than the regression method [2,14,15]. However, there are difficulties related with their poor extrapolation accuracy and it is necessary to train models properly, requiring experimentation using a wide range of possible working conditions [11]. Therefore, is necessary to apply a tailor-made procedure for training ANN and to focus the attention on improved training algorithms and network topology for the best training result [16].

Presented in this paper is an ANN-based model able to predict online the resultant cutting force under actual cutting conditions. The model describes the dynamic response of the plant output (resultant cutting force) before changes in the plant input (feed rate command and depth of cut).

A few experimental tests to obtain the data to be used in the training phase are required because of the utilization of standard workpiece with an irregular profile in the depth of cut. It allows the sufficient excitation of the system. In addition, a combined

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excitation (feed rate, spindle speed, depth of cut) during a short period of time, considering tool and material, contributes to an easier data acquisition (low data volume to be post-processed). The integration of process parameters and variables in the model or a set of models will favor the full characterization of cutting force behavior in normal and abnormal tool conditions.

Using this model, easily obtained from straightforward machining test, further refinements of monitoring systems and new developments of complex adaptive controllers can be carried out. Furthermore, it can also be used for designing and evaluating the performance of the controllers under variations in the milling process dynamics. The utilization of an internal sensor signal (indirect measurement of cutting force from spindle drive current) ensures a fast response, reduces the synchronization problems and installation effort so-called Multilayer Perceptron (MLP)[7]. For suitability to all neural network applications is the of the most widely used paradigms for its made, aiming at the type of ANN used herein. One

\[ \hat{y}_i(w, W) = L_i \left[ \sum_{j \in I} w_{ij} h_j(w) + W_{\theta i} \right] \]

(1)

where \( q \) is the number of output neurons, \( M \) is the number of neurons in the hidden layer, \( w \) are the inputs, and \( \hat{y}_i \) is the output of the net.

The weights are specified by the matrices \( w \) and \( W \). Both matrices can be included in the weight matrix \( \theta \). Consider the training set:

\[ z^N = \left( \begin{array}{c} u(t) \\ y(t) \end{array} \right) \theta = \left( \begin{array}{c} w \\ W \end{array} \right) t = I,...,N \]

(2)

The identification problem can be viewed as the determination of the mapping from the set of data \( z^N \) (training set) to the set of possible weights (\( \hat{\theta} \)) so that the network can produce a prediction \( \hat{y}(t) \) as close as possible to the actual output \( y(t) \)[10].

\[ z^N \rightarrow \hat{\theta} \]

(3)

Using the approach called prediction error:

\[ V_N(\theta, z^N) = \frac{1}{2N} \sum_{t=1}^{N} (y(t) - \hat{y}(t|\theta))^2 \]

(4)

The weights are calculated:

\[ \hat{\theta} = \arg \min V_N(\theta, z^N) \]

(5)

As the training algorithm a version of the Levenberg-Marquardt method was selected [3].

\[ R(t) = R(t-1) + (1/y(t)|D(t)|y(t)|D(t)|^{-1} + \delta I - R(t-1)) \]

(6)

\[ \hat{\theta}(t) = \hat{\theta}(t-1) + \gamma(t) \cdot \theta(t-1) \cdot D(t) e(t) \]

(7)

where \( R(t) \) is the Hessian approximation in Gauss-Newton algorithm, \( \gamma(t) \) is the gain, \( D(t) \) is the gradient of the predictions computed with respects to the weights, \( \delta \) is a positive number, and \( \hat{\theta}(t) \) is a recursive estimate of the weights, based on the data up to time \( t \).

2. Milling process model.

Force measurement is important to monitor the cutting process. The cutting force is considered the variable that best describes the cutting process. Cutting force monitoring is frequently used to detect tool wear and breakage. On the other hand, its regulation (i.e. mean cutting force control) is closely related to metal removal rate (MRR) improvements and the optimization of machining processes.

If the cutting force is directly and accurately measured, or indirectly measured from spindle drive current consumption, the quality and geometric profile of the cutting surface can be evaluated from the force pattern. Additionally, oscillatory responses and peaks in the cutting force pattern can be the result of abnormal high loads, what would indicate a process

**Figure 1. Scheme for milling process optimization.**

In section 1 a brief presentation of neural networks that focuses on the kind used, including training algorithm, is given. In section 2, a brief description of the milling process and its general characteristics is shown. In section 3 the experimental set-up, the design considerations and the network topology for the best training result obtained are presented. Finally, we conclude on the model suitability and some suggestions for its further improvement and future works.

1. Brief description of the ANN.

For the sake of clarity, a brief introduction will be made, aiming at the type of ANN used herein. One of the most widely used paradigms for its suitability to all neural network applications is the so-called Multilayer Perceptron (MLP)[7]. For simplicity and in consideration of an eventual real-time implementation the class of MLP considered here consists in only one hidden layer with hyperbolic tangent activation function \( H \), and a linear activation function \( L \) in the output.
irregularity and an increase danger for tool breakage or workpiece damage.

2.1 Milling process model from a classical viewpoint.
Due to the complexity and uncertainty of the milling process the numerous experimental and practical solutions in the field of tool condition monitoring and adaptive control have only a limited application [17].

Machining process uncertainty is affected by several factors such as the condition of the tool used for metal removal, variation in tool holders and the variability in the part material itself. In this context, a precise mathematical model can provide a very efficient characterization of the dynamic behavior of the milling process and it serves as a foundation for an accurate investigation and analysis of the machine tool performance and its limitations.

The milling process dynamics (cutting force response to changes in feed rate) can be modeled using, at least, a second order differential equation. As a result, a second order model that relates the cutting force ($F$) with feed rate ($f$) is reported in the literature [9]:

$$\frac{d^2 F}{dt^2} + 2\xi(t)\omega_n \frac{dF}{dt} + \omega_n^2 F(t) = K_n(t)\omega_n^2 f(t) \quad (8)$$

where, $\xi$ is the damping ratio, $\omega_n$ is the natural frequency and $K_n$ is the process gain.

The coefficients of this differential equation are very sensitive to changes in the cutting process. The damping ratio, $\xi$, grows linearly with the depth of cut (DOC), and decreases slightly with spindle speed ($s$). The gain, $K_n$, varies nonlinearly with DOC and decreases slightly with cutting speed. The natural frequency, $\omega_n$, also varies depending on cutting parameters. Up to date, different models have been obtained always using a second order differential equations [13]. These models have a narrow validity and they cannot go beyond certain limits in representing the process complexity and uncertainty.

2.2 Model based on neural networks.
The need to predict cutting forces for purposes of process planning, including surface accuracy and tool condition monitoring, motivates the presently research. The occurrence of chatter and vibration in milling, and the need to avoid these effects, are other motivations for studying the dynamic behavior of the milling process.

The a priori knowledge about the process can be simplified by looking at the plant as a black box with its input-output variables, parameters, constraints and objectives [5]. Inputs can be subdivided into input variables ($s$ and $f$) and disturbances: material properties (hardness, machinability, etc.). Other spurious disturbances like variation in the power supply and parts wear, are also included. The type of cutting tool (diameters, number of teeth, material, etc.) and depth of cut ($a$) are considered process parameters. The output variable is the mean cutting force ($F$), and is related to the constraint given by the available power at spindle motor.

Considering the nonlinear system described by:

$$F(t+k) = G \left[ F(t),...,F(t-n+1);f(t),s(t),a(t),...,f(t-m+1),s(t-m+1),a(t-m+1) \right] \quad (9)$$

where $G$ is an unknown function that we would like to identify and $f, s, a$ and $F$, are the inputs and output respectively, $n, m \in \mathbb{Z}$. Consider a parallel identification scheme [12]:

$$\hat{F}(t+k) = \hat{G} \left[ \hat{F}(t),...,\hat{F}(t-n+1);f(t),s(t),a(t),...,f(t-m+1),s(t-m+1),a(t-m+1) \right] \quad (10)$$

where $\hat{G}$ represents the ANN input-output mapping and $\hat{F}(t+k)$ is the output of the identification model ($k$-ahead prediction).

In spite of possible instability, equation (10) will allow the carrying out of simulations and studies without the need of actually executing the cutting process. Therefore, knowing the profile that will be mechanized and actual cutting speeds, dangerous situations for the tool can be predicted.

3. Experimental set-up.
The experimental tests are conducted on a 5.8kW-4 axis milling machine equipped with CNC, which is
interfaced with a personal computer by an RS-232 communication link. The milling process, whose model is to be obtained, is endowed with a cutting-force regulation system with the feed rate \( f \) in the role of action variable. The feed rate \( f \) is generated online by a hierarchical fuzzy controller. Further details concerning this cutting force control system can be found in [4].

The input-output data for the model identification are obtained from the feed rate command signals and spindle actual drive current signal (i.e. the armature current signal from DC spindle motor, at 1000 Hz sampling frequency). A calibration library provides actual values of \( F \) [4]. Necessary filtering is done by means of a low-pass filter. At this point, it is worthwhile to reiterate that the model objective is to predict in real-time, one step ahead, the resultant mean cutting force \( \hat{F} \).

For the experimental works, only new milling cutters are used. A two-fluted milling tool 25mm in diameter is chosen. Two workpieces with several disturbances in the depth of cut are chosen intentionally for training ANN (see fig. 3A) and online running of the model (see fig. 3B). For the experiments, the spatial position of the cutting tool is always kept at a constant vertical tool position. Slot milling operation is supposed to be done in one direction only.

![Figure 3](image)

**Figure 3** Workpieces for training (a), and validation tests (b).

### 3.1 Training and verification methodology.

Among the data measured from the milling process are the time-varying multi-frequency structure and the time varying mean value, which must be considered to generate a more complex model in order to fit various physical situations.

A preliminary processing was applied to the data before performing the training procedure [1]. Such tasks as the standardization (mean value and standard deviation of the cutting force signal) and the digital filtering by means of a finite impulse response filter (FIR) were performed. The training algorithm was developed using MATLAB. The topology was initially chosen as follows: two inputs \( f \) and \( a \), one output \( \hat{F} \), a linear activation function at the output, and one hidden layer using hyperbolic tangent for the activation function. The type of model selected was created starting from the *a priori* knowledge of the milling process and the types of models considered in previous works (see fig. 5A). An ANN with 6 neurons in the input, 12 neurons in the hidden layer and 1 in the output layer, was selected.

The initial values of the weights were randomly chosen. Training of the network was stopped when the error \( e \) reached 0.001. The initial cutting conditions used were \( f_o = 100 \text{ mm/min}., \ s_o = 1000 \text{ rpm}, \ a_{max} = 12 \text{ mm} \) conditions. Real-time control action (i.e. \( f \)), performed by hierarchical fuzzy controller to increase the MRR in the milling operation and the actual value of depth of cut \( (a) \), were used for an off-line training of ANN. At the end of the training stage a pruning algorithm was performed in order to optimize the size of the network, removing the superfluous weights [6]. In order to validate the model, data analysis (mean square value analysis, auto correlation analysis and transient data study) were done. First, the validation was performed on the training set (see figure 4B). It can be inferred that the selected model structure contains enough neurons and the order of the model is adequate. Figure 4C shows that predictions are close to the measure data (auto-correlation function of prediction errors and cross-correlation of \( f \) and \( a \) with prediction error).

We also examined the robustness property of the model against changes in cutting conditions (material hardness, tool wear, disturbances in \( a \)). Additionally, real-time performance of the model on these situations was investigated. Verification tests were performed considering new, semi-worn and worn tools in slot milling operation made upon another profile (see figure 3B).
Figure 4 A) Model structure B) Validation on training set, C) correlation functions.

Figure 5 depicts the experimental results of the cutting force prediction by the model of two different cases of tool condition (i.e. worn and semi-worn). The actual cutting force $F$ (solid line), the prediction of cutting force $\hat{F}$ (dashed line) one step ahead, the actual depth of cut ($a$) and feed rate ($f$) are shown in this figure. By comparing the plots it can be observed that the model can predict $\hat{F}$ with acceptable accuracy in spite of tool condition. The real time behavior of the model, when slot-milling operation is carried out on another workpiece with a new tool is illustrated in figure 6.

<table>
<thead>
<tr>
<th>Validation tests</th>
<th>New tool (fig. 6)</th>
<th>Semi-worn tool (Fig. 5A)</th>
<th>Worn tool (Fig. 5B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$MSE [%]$</td>
<td>4.66</td>
<td>5.46</td>
<td>10.2</td>
</tr>
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</table>

Table 1. Performance index for evaluating the behavior of model.

Table 1 summarizes the $MSE$ (mean square error) criterion that is very similar in all validation tests. Good properties of the model can be inferred from these results, as well as its generalization capability.

This dynamic neural network-based model provides sufficiently accurate prediction of cutting force, since the process-dependent specific dynamic properties of slot milling operation are adequately reflected.

Figure 5. Real-time behavior of the model considering different condition of tools A) semi-worn and B) worn tool.

Figure 6 Response of the model considering another profile.
CONCLUSIONS

The model presented in this paper constitutes a previous and natural step in order to predict the tool condition. Its effective application allows the real time prediction of undesirable oscillations, harmful to the quality of finished product and cutting tool integrity. The outcomes, when three conditions of tools (new, semi-worn and worn) are examined, demonstrate the suitability of this model. Based on this model and a decision-making procedure, it is possible to continuously check whether the cutting force is greater than a critical value, in which case, the tool can be damaged and the machine tool must be immediately shut down.

These results can be used for developing complex adaptive controllers and new tool condition monitoring systems. The development of decision-making methodologies to predict the tool condition needs to be studied, as well as different strategies with an emphasis in learning.

References