MULTI-PARAMETER ANN MODEL FOR FLAT-END MILLING

Hazim El Mounayri, M. Affan Badar, Gustavo A. Rengifo

Department of Mechanical Engineering
Purdue School of Engineering and Technology, IUPUI
Indianapolis, IN 46202
helmouna@iupui.edu; Tel.: 317-278-3320; Fax: 317-274-9744

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ABSTRACT
The quality, productivity and safety of machining can be significantly improved through the optimization of cutting conditions. The first step in achieving such an objective is the development of accurate and reliable models for predicting the critical process parameters. In this paper, an innovative Artificial Neural Network (ANN) model that predicts both cutting force and surface roughness in end milling is developed and validated. A set of five input variables is selected to represent the machining conditions while twelve quantities representing two key process parameters, namely, cutting force and surface roughness, form the variables of the network output. Full factorial design of experiments is used to generate data for both training and validation. Successful training of the neural network is demonstrated through comparison of simulated and experimental results for four different output variables, namely cutting force, surface roughness, feed marks, and tooth passing frequency. The predictive ability of the model is verified experimentally by comparing simulated output variables with their experimental counterparts. A good agreement is observed.

KEYWORDS: End Milling, Back Propagation Artificial Neural Networks (BPANN), Process modeling, Cutting Forces, Surface Roughness.

MULTIPARAMÈTRE ANN MODELE POUR FIN PLATE EN MOULANT

RÉSUMÉ
La qualité, productivité, et sécurité d'usinage peuvent être amélioré énormément à travers l'optimisation des conditions de coupure. La première étape pour arriver à ce but est le développement de modèles qui sont précis et qui peuvent prévoir les paramètres importants de l'opération. Dans cet article, un modèle nouvel qui utilise l'intelligence artificielle (ANN ou "Artificial Neural Network") et qui a la faculté de prédire la force de coupure et inégalité de la surface est développé et validé. Cinq paramètres d'entrée sont choisis pour présenter les conditions de coupure. Douze quantités représentant deux paramètres importants (la force de coupure et l'inégalité de la surface) sont les résultats du ANN modèle. Conception statistique d'expérience (DOE our "Design of Experiments") est utilisée pour produire les données pour entrainer et vérifier le modèle. L'abilité du modèle entrainé est prouvée à travers une comparaison entre les résultats simulés et les résultats expérimentales pour quatre variables de sortie (la force, l'inégalité de la surface, les marques de coupure et la fréquence de coupure). L'abilité du modèle de prévoir est vérifiée d'une façon expérimental à travers une comparaison entre les résultats simulés et les résultats expérimentales. Un bon accord est observé.
1. INTRODUCTION

Machining, which is key in manufacturing, basically consists of removing material from a workpiece in the form of chips. Machining is necessary when small and tight tolerances and surface finishes are required. Usually, most machining processes have low setup cost compared to other manufacturing processes such as molding or casting. However, cost increases when high volume machining is needed. Several manufacturing operations representing the metal cutting activity exist such as grinding, drilling, turning and, milling, the latter being the most used in the industry due to its versatility and applicability.

The milling operation is extensively used in many applications; the automobile and aerospace industries are clear instances. A variety of applications can range from very simple to final parts with complex geometry and shape, and high level of precision and surface qualities. In general, it is more complex to model milling than other types of machining processes.

Flat end milling is aimed at removing metallic material by two continuous motions, those of the tool and workpiece. Basically, the tool has a rotational motion (spindle speed) and the workpiece a linear one (feed rate), as shown in Figure 1. A cutting edge of the tool is in full contact at many points on two sides as well as at bottom of the material, which changes according to the position of the edge relative to the workpiece material. In general, a machined surface is the result of geometric and kinematics reproduction of the tool point shape and cutting trajectory. In the past, many efforts have been made to study the surface quality and/or accuracy of the material. In this work, effort concentrates on modeling the end milling operation based on the dynamics and the operational variables or cutting parameters of the process.

Several parameters are defined, including cutting speed, feed, depths of cut (radial and axial), and cutter diameter and geometry. These variables conjointly with the tool and workpiece material determine the state of cutting, which directly controls the values of the process parameters. The latter include cutting force, surface roughness, tool wear, machining time, vibration, tool life, etc. In practice, factors such as cutting conditions, tool geometry, machine vibration, workpiece material and runout, affect the cutting force and surface finish of the workpiece surfaces. Cutting force is one of the most important process parameters used to simulate the milling process, as it relates to tool wear, tool breakage and chatter vibration. On the other hand, surface roughness is described as the outcome effect of the cutting force in terms of the effects on the dimensional precision of the machined surfaces. Therefore, controlling the process machining parameters is very important in meeting the quality and productivity requirements.

![FIGURE 1: The end milling operation: Definition of cutting parameters](image-url)
Currently, the selection of cutting tools and machining parameters is either done by trial and error, based on experience or from reference handbooks. When inaccurate cutting parameters are used, the safety of the process as well as the quality of the final product are put at risk. Therefore, fundamental knowledge of the milling operation involving new tool designs and sophisticated manufacturing models to optimize the cutting conditions and control the process parameters is required. End milling models based on the geometric and physical characteristics of the process have been implemented in the past mostly for cutting force prediction. However, due to the non-linearity and complexity of the process, the force modeling, whether analytical or mathematical, typically lacks accuracy and generality.

A relatively new technique has shown the potential of overcoming the above limitations. Artificial Neural Network (ANN) approach is able to model highly non-linear systems through training from a representative data set. By minimizing the data set needed for training, we can also turn ANN model development into an efficient process. Compared to mathematical and analytical models (i.e. traditional methods), ANN offers simplicity and speed while maintaining system accuracy.

The current work takes advantage of ANN to develop a unique, accurate, efficient, inexpensive, practical, and more comprehensive 2½-axis end milling model, capable of simulating and predicting both cutting force and surface roughness.

2. LITERATURE REVIEW

Extensive work has been conducted for modeling end milling process based on mathematical, semi-empirical or mechanistic approaches. Altintas [1] developed an adaptive control model to maintain surface accuracy based on combined dynamics of feed motion and part geometry. Sutherland et al. [2] created an algorithm to determine chip load for surface error prediction. Kline et al. [3] predicted surface error profile using mathematical models for the cutting force system and cutter/workpiece deflection that included machining conditions, geometry and material properties of both the cutter and workpiece. Ryu et al. [4, 5] developed an effective method to predict the form error in side wall machining from mathematical models of tool deflection and cutting forces, considering tool geometry, tool setting error and machine tool stiffness. Later, they extended to the generation of end milling surface profiles through a fundamental approach of vectors transformations considering tool runout, tool deflection, and tool setting error. Schmitz et al. [6] explored the effects of milling cutter eccentricity/run out on surface topography and cutting forces. In general, machining process mechanistic models intend to model the cutting force components in terms of two elements: the physical and the geometric aspects of the cutting process, without establishing any analytical relationship. On the other hand, mathematical models focus on the functional approximations of collected experimental data. It is however difficult to develop an accurate and general model of the end milling model using these traditional techniques.

In view of the above, there is need for an efficient approach which can model the non-linear end milling process accurately. The non-traditional approach proposed herein is, ANN. This relatively new technique has been widely used to model, monitor and control metal cutting, especially end milling. The basis of this advanced approach is the interaction of numerous simple adaptive elements or entities in order to build complex adaptive systems. ANN has the main characteristics of capturing complex input-output relationships by learning from data that represents the behavior of a system. ANN models can in principle be trained to include the effects of any number of input parameters as well as predict any number of process outputs.
without increasing the complexity of the solution. Several researchers have demonstrated the
ability of neural networks models to successfully develop implicit relationships between sets of
inputs and outputs. More specifically, Liu et al. [7] developed a feed forward ANN algorithm to
predict flank wear in orthogonal turning using as input cutting parameters, feed rate, cutting
speed and force ratio. Similarly, Elanyar et al. [8] applied ANN to implement a machining
condition monitoring model for automation and prediction of tool wear and surface roughness.
Recently, Oktem et al. [9] used integrated artificial intelligence tools (neural networks and
genetic algorithm) to determine best cutting parameters which could lead to minimum surface
roughness. El-Mounayri et al. [10] developed accurate ANN to predict instantaneous cutting
forces in both flat and ball end milling, considering feed, speed and depth of cut as cutting
parameters. Similarly, Dugla et al. [11] used various ANN techniques to predict surface
roughness.

ANN should, in principle, be able to model the end milling process accurately and capture
the dynamic characteristics of the process since it is trained and validated with real
experimental data.

3. CURRENT APPROACH: BPANN

In the current work, BPANN (Back-Propagation ANN) is used for the modeling of the
instantaneous cutting forces and surface roughness in end milling. BPANN is a gradient descent
algorithm where the gradient is computed for non-linear, multilayer ANN. The general network
topology of BPANN is composed of an input layer, one or more hidden layers using log-sigmoid
transfer function and an output layer with linear transfer function (Figure 2). Each layer is
arranged by neurons or processing elements (PE) operating in parallel and connected to other
layers through the weight lines that come from each PE (Figure 3). The PE's are the
components of the ANN where the computation is carried out.

![Figure 2: Back propagation network topology](image)

BPANNs tend to give reasonable results when sets of inputs have never been presented to
the network. In general, a new set of inputs will lead to the generation of an output that is similar
to the correct output for input vectors used in the training. The adaptation process used by
BPANNs is done at the end of each epoch, which guarantees that the order in which the
patterns or set input/outputs are presented to the network does not influence the training. The
operation of BPANNs is performed generally through two major phases, the feed forward phase and the back propagation phase.

FIGURE 3: Architecture of a processing element “PE”

Feed Forward Phase

In this phase the input patterns which are represented by the input PE’s connect to the set of neurons or PE’s of the hidden layer(s). The information is conducted from the \( i^{th} \) input PE to the \( j^{th} \) PE in the hidden layer through the weight \( W_{ij} \). As shown in Figure 3, the incoming data or information, in such element, is represented by equation (1),

\[
a_j = \sum_{i=0}^{n} W_{ij} I_i
\]

where, \( a_j \) is the linear combination of each \( I_i \) multiplied by the weight \( W_{ij} \); \( I_i \) is the \( i^{th} \) input; \( W_{ij} \) is the weight value from the \( i^{th} \) input PE to the \( j^{th} \) hidden PE and \( n \) is the number of incoming inputs to the \( j^{th} \) PE. Then, this incoming data \( a_j \) is the value fed to the squashing or transfer function which gives the output of the \( j^{th} \) PE to the next hidden layer(s). The output of this element is given by equation (2),

\[
Y_j = SF^l(a_j)
\]

where, \( Y_j \) is the output value of the \( j^{th} \) element; \( SF^l \) is the squashing or activation function of the \( j^{th} \) hidden layer. The value of \( Y_j \) is propagated through each further layer until the output is generated.

Back-Propagation Phase

In the Back-Propagation phase of the BPANNs, the learning process of the algorithm is conducted. The method consists of updating the network weights in the direction in which the performance of the gradient decreases most rapidly. The output simulated \( (Y_j) \) is calculated through equation (2) and then compared with the target value \( (t_j) \) using equation (3):

\[
e_j = \frac{1}{2}(t_j - Y_j)^2
\]
Since the error calculated corresponds only to one output PE, the overall error of the phase is composed of the errors of the outputs of the PE, expressed by equation (4):

\[ E = (e_t, \ldots, e_j, \ldots e_k) \]

\( k \) being the number of outputs.

The error is then transmitted backwards from the output layer to the input layer. The PE's update the connection weights in order to lead the convergence of the network. In this study, the Levenberg-Marquardt technique is employed which allows the adjustment of the network weights at each epoch, and approaches second order training speed without much added computational expense. The weight updates are based on equation (5):

\[ W_{ij}^{new} = W_{ij}^{old} - \frac{J^T \cdot \delta}{J^T J + \mu \cdot I} \]

where, \( W_{ij}^{new} \) and \( W_{ij}^{old} \) are the corrected and previous weight for \( j^{th} \) PE coming from the previous layer respectively, \( J \) is the Jacobian matrix containing the first derivatives of the network errors with respect to the network weights and error signals for the \( i^{th} \) pattern, \( \mu \) is the scalar factor, and \( \delta \) is the error signal for the \( j^{th} \) PE.

4. EXPERIMENTAL DATA FOR TRAINING AND VALIDATION

Experimental Setup
The machine tool used for all the experiments conducted in this work is a FADAL® VMC 3016L 4-Axis CNC Milling machine. The workpiece material considered was Aluminum grade 7075T6. The experiments were conducted using 1-flute, HSS, Do-All® end mills with tool geometry parameters 14° rake angle, a 16° primary clearance angle, and a 37.5° helix angle. A one-flute-cutter was selected to eliminate the effects of cutter runout in this study (chip load of tool individual cutting teeth varies periodically, increasing the roughness and scalloping of machined surfaces). This type of tool is designed specifically for non-ferrous metal machining, e.g. aluminum and so has a higher rake angle. Down milling was used with the coolant on.

Cutting forces were measured using a 3-component force dynamometer by Kistler, Type 9257B, which provides the sensitivity and rigidity needed for accurate measurement of the three orthogonal force components (Figure 4).
After milling and measuring the cutting forces, the resulting surface profile was also measured at two different levels (Figure 5) using a non-contact profilometer, Proscan 2000, equipped with a chromatic sensor and resolution of 0.1 μm (Figure 6). Measurements were taken along a scanning path of 3 mm long by 1 μm width with a sensor sampling rate of 300 Hz.

FIGURE 4: Setup for measuring cutting force

FIGURE 5: Surface Profile measurements at two levels

FIGURE 6: Profilometer used for the surface measurement
Full Factorial Design of Experiments

The cutting parameters selected as control factors of the milling process were, the cutter diameter, depths of cut (radial and axial), cutting speed and feed per tooth. The ranges of each parameter were obtained from the Institute of Advanced Manufacturing Sciences Machining Handbook. Each range was divided into orthogonal and equally space levels. Cutting force variation with respect to time and surface profiles were measured for each combination of levels. A full factorial design $2^3*3^3$ with a total of 384 experiments was performed with the following configuration:

- Tool Diameter (D): 12.7 and 25.4 [mm] (1/2 and 1 inches)
- Axial Depth of Cut (ADC): 25%, 50%, 75% and 100% of the tool diameter [mm]
- Radial Depth of Cut (RDC): 0.5, 2, 4 and 6 [mm]
- Feed per Tooth (F): 0.1, 0.15, 0.2 and 0.25 [mm/tooth]
- Cutting Speed ($v$): 90, 110 and 150 [m/min].

Data Pre-Processing

In the simulation of the milling cutting force and surface roughness, it is necessary to estimate the relevant variables representing the process responses given a set of input parameters. For this matter, some preprocessing of the raw data has to be conducted.

Cutting Forces

The following output variables are computed for each component of the instantaneous cutting forces collected (along the X direction “Fx”, Y direction “Fy” and Z direction “Fz”). The period is averaged out from the periods of the force component signal.

- Amplitude (Amp.) (Fx, Fy, Fz)
- Mean (Mean) (Fx, Fy, Fz)
- Standard deviation (Std.) (Fx, Fy, Fz)
- Period (Avg. Period)

Surface Roughness. Surface roughness “Ra” and feed marks (inscription of the tool tooth that is left after it completes a full rotation) were computed at each level of the experiments. Average of both levels is used to define the surface roughness output variables. The measured output variables corresponding to the surface profiles are,

- Surface roughness (Ra)
- Feed marks (FeedM)

Normalization

Before training and validating the BPANN, input and output sets are normalized in order to make the data suitable for the training process. Equation (6) is used to map each variable set to a value between 0 and 1.

\[ N = \frac{(R - R_{\text{min}}) * (N_{\text{max}} - N_{\text{min}})}{(R_{\text{max}} - R_{\text{min}})} + N_{\text{min}} \]  

where, $N$, is the normalized value of the variable, $N_{\text{min}}$, is the minimum value of normalization (0), $N_{\text{max}}$, is the maximum value of normalization (1), $R$, the real value of the variable, $R_{\text{min}}$, the minimum value of the variable set and $R_{\text{max}}$, the maximum value of the variable set.
5. ANN MODEL TOPOLOGY & RESULTS

ANN Model topology
A BP ANN model for predicting two main process parameters (cutting force and surface quality) is designed. Multiple quantities were used to represent these parameters. On the one hand, force was described using the mean, mean amplitude, and standard deviation of all three force components ($F_x$, $F_y$, and $F_z$). On the other hand, surface finish was expressed in terms of surface roughness and feed marks. The resulting topology is shown below (Figure 7).

Training and Validation Sets:
Once the data is pre-processed and normalized, the BPANN can be trained on mapping the functional pattern between the input and output vectors previously defined. The network (Figure 7) is trained with only 75% of the data collected, or 288 experiments (Training Set). The remaining 25% of the data (96 experiments) corresponds to the Validation Set which is used to test the functional relationship evolved by the BPANN.

Training Results:
The network topology used for the training and validation of the BPANN is integrated by an input layer with 5 PE's, 3 hidden layers with 22 PE's each and an output layer of 12 PE's. The performance of the training phase between the network responses and the corresponding measured real target values is measured by two methods, the computation of the error
(equation 7) and the linear regression analysis coefficient (R). A value of R equal 1 indicates that the network is perfectly simulating the training set while 0 means the opposite.

\[
e_j = \frac{\sum_{i=1}^{288} \left| \frac{t_{ji} - Y_{ji}}{t_{ji}} \right|}{288} \times 100\%
\]

(7)

where, \(e_j\) is the average error of the output variable \(j\), \(t_{ji}\) is the target value of the output variable \(j\) and experiment \(i\), \(Y_{ji}\) is the predicted or simulated value of the output variable \(j\) and experiment \(i\), \(i\) is index of the experiment number, and \(j\) is the index of the output variable number.

The training phase of the BPANN was successfully completed in 16 epochs. The error \(e\) and \(R\) values for all the outputs were obtained to check on simulation accuracy between the real the predicted values (Table 1). The training simulation shows that the experimental and simulated values are well in accordance with each other. The network mimics the output variables accordingly with the target values. The calculated mean error for the training phase was 3.88%. The output variables Mean of Forces Fx and Fz were the most difficult to get trained with training errors greater than 6%. In contrast, Surface Roughness and Period were the output variables with most success, as they trained with only 1% of training error. Training performance of output variable Mean of Force Fx is shown in Figure 8.

![Training results, Target – output comparison: Fx mean](image-url)
Validation Results

After having trained the model, the BPANN is validated with the validation set (96 experiments). The error and the line regression analysis (R) are used as measures to estimate the accuracy of the model. The validation results for all 12 output variables are shown in Table 2. The output variable Surface Roughness shows a very high simulation error when comparing predicted with target values. In fact, percentage error reaches as high as 33%. However, the mean of the BPANN validation phase error is about 10.5%. The validation performance is presented in Figure 9.

6. DISCUSSION OF RESULTS

The training phase of the end milling BPANN model was successfully completed. The system was effectively and accurately trained in 16 epochs using topology architecture of 3 hidden layers with 22 PE's each. Table 1 shows that the highest percentage error in the training phase corresponds to the output variables “Mean of Forces Fx, Fy and Fz”. All R-values of the regression analysis are over 0.9, which means that there is a good correlation between the outputs simulated by the network and the target values.

**TABLE 1: Error and Linear regression (R) values for the BPANN training phase**

<table>
<thead>
<tr>
<th>Output</th>
<th>Avg.</th>
<th>R value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fx Amp.</td>
<td>3.18</td>
<td>0.99928</td>
</tr>
<tr>
<td>Mean</td>
<td>6.38</td>
<td>0.99896</td>
</tr>
<tr>
<td>Std.</td>
<td>3.38</td>
<td>0.99944</td>
</tr>
<tr>
<td>Fy Amp.</td>
<td>3.29</td>
<td>0.99847</td>
</tr>
<tr>
<td>Mean</td>
<td>5.84</td>
<td>0.99837</td>
</tr>
<tr>
<td>Std.</td>
<td>2.87</td>
<td>0.99922</td>
</tr>
<tr>
<td>Fz Amp.</td>
<td>3.78</td>
<td>0.99894</td>
</tr>
<tr>
<td>Mean</td>
<td>6.78</td>
<td>0.99907</td>
</tr>
<tr>
<td>Std.</td>
<td>3.82</td>
<td>0.99996</td>
</tr>
<tr>
<td>Period</td>
<td>1.54</td>
<td>0.99893</td>
</tr>
<tr>
<td>Ra</td>
<td>1.45</td>
<td>0.99955</td>
</tr>
<tr>
<td>Feed Marks</td>
<td>4.21</td>
<td>0.98757</td>
</tr>
</tbody>
</table>

**TABLE 2: Error and Linear regression (R) values for the BPANN validation phase**

<table>
<thead>
<tr>
<th>Output</th>
<th>Avg.</th>
<th>R value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fx Amp.</td>
<td>8.54</td>
<td>0.99153</td>
</tr>
<tr>
<td>Mean</td>
<td>12.78</td>
<td>0.99019</td>
</tr>
<tr>
<td>Std.</td>
<td>8.53</td>
<td>0.99273</td>
</tr>
<tr>
<td>Fy Amp.</td>
<td>8.32</td>
<td>0.99161</td>
</tr>
<tr>
<td>Mean</td>
<td>8.72</td>
<td>0.99140</td>
</tr>
<tr>
<td>Std.</td>
<td>7.38</td>
<td>0.99533</td>
</tr>
<tr>
<td>Fz Amp.</td>
<td>8.50</td>
<td>0.98811</td>
</tr>
<tr>
<td>Mean</td>
<td>10.43</td>
<td>0.98481</td>
</tr>
<tr>
<td>Std.</td>
<td>9.23</td>
<td>0.98696</td>
</tr>
<tr>
<td>Period</td>
<td>6.11</td>
<td>0.99484</td>
</tr>
<tr>
<td>Ra</td>
<td>32.59</td>
<td>0.47328</td>
</tr>
<tr>
<td>Feed Marks</td>
<td>5.58</td>
<td>0.97603</td>
</tr>
</tbody>
</table>
Similarly, accurate results were obtained in the validation phase of the BPANN model. In general, there is good agreement between the predicted output responses and the corresponding experimental target values. All the values of the regression analysis were above 0.9 except for the surface roughness. The prediction of the surface roughness was achieved with a percentage error of 32.6%. The modeling and simulation of this process parameter is considerably difficult, given the very definition of the surface roughness. In fact, surface roughness could be defined as the “arithmetical average” of the height of the finely spaced machined surface irregularities. Therefore, averages or means can sometimes be very difficult to be model because the data can be affected locally. Overall, the simulated results of the BPANN obtained represent an improvement over the published work, especially considering that the model fully and efficiently predicts both cutting force and surface roughness. For instance, El-Mounayri et al. [12] and Dugla et al. [11] predicted only surface roughness “Ra” with an accuracy of 82% and 53% respectively, while the current work’s BPANN model predicts end milling significant process parameters, Cutting Force and Surface Roughness with accuracy of 89.5%.

7. CONCLUSIONS AND FUTURE WORK

Despite the common use of end milling in the manufacturing industry, general and reliable models that could optimize this operation are not readily available. An approach which considers the simulation of the physical aspect of the process is required. However, this task is not easy to accomplish, due to the multidimensional nature of end milling and non linear relationship among its process parameters. The selection of cutting tools and machining conditions has a significant impact on the overall machining efficiency and process reliability. Previous research work has focused on the development of empirical and analytical end milling models. However, these studies appear to be limited in applicability and generality, since no
information related to the physical aspects of the process is usually included. In this work, the limitations of the current end milling process simulation are addressed by focusing on the development of a general, complete, efficient and accurate predictive end milling model for two key parameters, namely cutting force and surface roughness. Furthermore, as opposed to previous work, the simulation of cutting force parameters is based on the prediction of responses per force component (i.e. amplitude, mean, standard deviation and period of X, Y and Z components); thus reconstruction of cutting force signal can be done. Previous research works were limited to the prediction of resultant cutting forces.

In spite of the encouraging results accomplished in the current work, it is important to clarify its limitations and at the same time recommend directions for future research. While the essential topology of the BPANN will remain the same, the end milling model could be extended by including additional input-cutting and output-process parameters. Number of cutting flutes, rake and primary clearance angles, among other parameters and/or additional critical process responses such as flatness, chatter, tool wear and geometric tolerances would significantly contribute to the expansion of the present end milling model and the development of machining industrial self monitoring and control systems. In addition, the application of the developed predictive force and surface roughness model to similar cutting tools such as ball and taper end mills would add more capabilities to the technique and make it more attractive for implementation in industry.

8. REFERENCES

