*Key Engineering Materials Vols 651-653 (2015) pp 1165-1170*
*© (2015) Trans Tech Publications, Switzerland*
*doi:10.4028/www.scientific.net/KEM.651-653.1165*

*Submitted: 2014-11-28*
*Revised: 2015-02-13*
*Accepted: 2015-02-15*

# Uncertainty management of cutting forces parameters and its effects on machining stability

Edouard Rivière Lorphèvre [a], Christophe Letot [b], François Ducobu [c], and Enrico Filippi [d]

University of Mons, Faculty of Engineering, Machine Design and Production Engineering Department, Place du parc 20, Mons, Belgium

[a]edouard.riviere@umons.ac.be, [b]christophe Letot@umons.ac.be, [c]francois.ducobu@umons.ac.be, [d] enrico.filippi@umons.ac.be

**Keywords:** Machining, cutting forces, heterogenous material, stability lobes.

**Abstract.** Virtual manufacturing is a field of research which numerically simulate all the manufacturing processes seen by a mechanical part during its production (for example casting, forging, machining, heat treatment,...). Its use is rising on various industries to reduce production costs and improve quality of manufactured parts. One of the most challenging component of the whole simulation chain is the simulation of machining operations due to some of its specificities (need of material law at high strain, strain rates and temperature, heterogeneities of machined material, influence of residual stresses,...). In order to circumvent these difficulties, macroscopic models of machining process have been developed in order to compute more global information (cutting forces, stability of the process, tolerance or roughness for example). For this approach, the cutting forces computation is done by using simple analytical law based on mechanistic approach. The parameters of the models have no clear physical meaning (or at least cannot be linked to intrinsic properties of the material to be machined) and are therefore considered constants for a given set of simulations. The aim of this paper is to take into account the uncertainty on the variability of the cutting force signal during machining operation used as input for mechanistic model identification. The variability of the response during a test on fixed conditions (cutting tool, machined material and cutting parameters) is taken into account to develop a model where parameters of the model can evolve during a given operation. The proposed model is then used as an input of a milling operation simulation in order to study its influence on machining stability as compared to a classical approach.

## Introduction

In order to reduce the production costs, simulation of manufacturing techniques has an increasing role for industrial application. These simulation tools (often referred as 'virtual manufacturing') are useful to reduce setup procedure by limiting the number of trials and errors necessary to find optimal operational parameters. Some manufacturing processes already use reliable methods for production testcases [1] but machining often break the numerical chain [2].
Machining operation simulation has to face several problems linked to complex material behavior (high strain, strain rate and temperature of the material), complex geometry of tools and/or part and dynamic modelling issues so currently simulation is not able to model all industrial testcases.
Generally speaking, two main approaches are used for machining simulation: mesoscale simulation and macroscale simulation. Both methods have advantages and drawbacks:

- mesoscopic approach tends to simulate physical phenomena happening during chip formation. In addition to cutting forces, several other aspects can be studied such as chip morphology, temperature, surface integrity or tool wear [3, 4]. These models are often limited to simple geometries (abundant literature is dedicated on 2D orthogonal cutting) due to the intensive computation time required.

- macroscopic models use simple analytical laws to model machining process interactions. Several models for orthogonal cutting have been used in the literature [5] (linear relation between chip section and forces, exponential model, model taking friction of the chip on cutting edge into account, ... ) and generalization to oblique cutting has also been performed [6]. These models are easier to compute, so more complex geometries can be used to solve coupled problems (stability and chatter vibrations, form error, ...). These models are anyway more limited because experimental test must be performed to get the actual values of the parameters of the model.

The aim of this paper is to improve the results of the macroscopic approach by taking into account the variability observed during experimental measurement of cutting forces in milling

## Variability on cutting forces

Experimentally speaking machining does not give constant output for a given set of experimental parameters. The cutting forces can be modified by global factors (small variation of cutter geometry, tool material or composition of workpiece). But in addition, during a given experimental test, variation can be observed due to heterogeneity of the material for example [12, 13].
In order to quantify this variability, the correlation between signal recorded for several revolutions of the tool is studied. The measured signal is resampled at a frequency which is a multiple of the spindle frequency to perform the computation. Root mean square criterion is used to assess the dispersion of results:

$$RMS_i = \sqrt{\frac{1}{n}\sum\left(F_{i,j}-\overline{F_i}\right)^2} \qquad \overline{F_i} = \frac{1}{n}\sum_{i=1}^{n} F_{i,j} \tag{1}$$

$i$ is the direction of the force (x,y or z), $j$ is the sampled position of the test ($n$ samples during one cutting test). By selecting several values close to programmed spindle speed, the effective spindle speed during the experimental tests (that may be slightly different to the programmed spindle speed) can be found as the value minimizing this criteria.

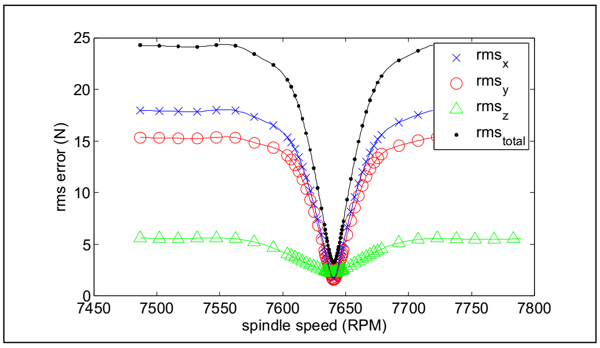

Fig. 1: Evolution of RMS with respect to spindle speed.

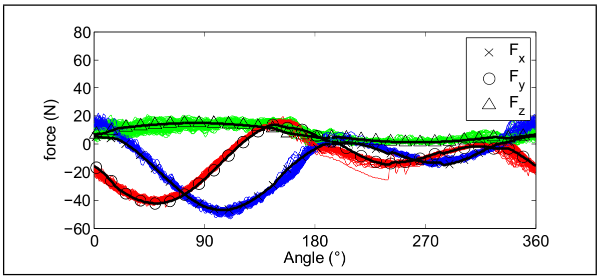

Fig. 2: Dispersion of experimental measurement over 300 revolutions of the tool for slot milling.

A series of experiments using Ti6Al4V titanium alloy have been recorded with a 2 mm diameter carbide tool (SECO 512020Z2.0-SIRON-A). Experimental tests were carried using cutting speed ranging from 48 to 72 m/min and feed ranging from 4 to 7 $\mu m$ per tooth. Slot milling and shoulder milling (RDOC of 1 mm) have been performed. The main testcase for this paper is a slot milling test at 60 m/min cutting speed and 6 $\mu m$/tooth feed. The evolution of the RMS value with respect to the spindle speed (Fig. 1) shows monotonous evolution, the optimal spindle speed is 7640 RPM. A figure superimposing force signal for each revolution of the tool on a single plot can be made to see the dispersion of the measurements for the optimal solution (Fig. 2).

## Inverse analysis

In the macroscopic simulation of the milling process, the most common approach to simulate the cutting forces along the complex shape of a cutter is to divide the tool into infinitesimal slices along cutter axis [6]. On each of these slices, the elementary cutting forces are computed on three orthogonal directions (*t:* along the cutting speed, *r:* along the local normal to the cutter and $a$: orthogonal to *r* and *t*) using simple analytical laws depending on macroscopic quantities (depth of cut, undeformed chip thickness,...). For this paper, simple linear model has been used as shown in equations 2

$$F_t = K_t \cdot h \cdot dz \quad F_r = K_r \cdot h \cdot dz \quad F_a = K_a \cdot h \cdot dz \tag{2}$$

Coefficient $K_t, K_r, K_a$ are the specific pressure, $h$ is the unedeformed chip thickness (computed using kinematic model as presented in [11]) and $dz$ is the height of the slice. The geometric description of cutter with complex shape has been performed in [7] so all elementary efforts can be projected on a global frame and then analytically integrated along the cutting edges to obtain the global effort.
The parameters of analytical models are not easily retrievable from mechanical properties of the materials. Several authors developed methods to retrieve these parameters from experimental measurement [8, 9, 10]. The approach used in this paper is based on the fitting of analytical model on temporal measurement of cutting forces measured during machining. This model allows the identification of parameters for linear or nonlinear analytical laws and is also able to estimate runout of the cutter during experiment [11].

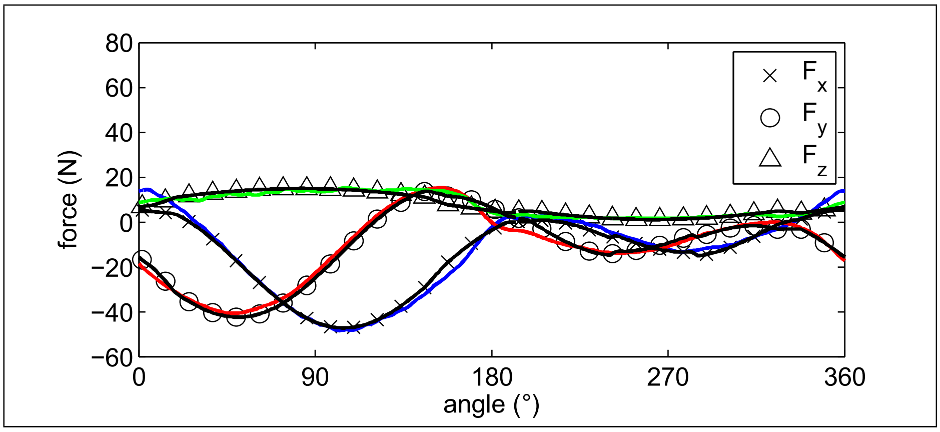

Fig. 3: Adjustment of signal over mean value for testcase 1.

In order to reduce the computation required by optimization, the mean value of the signal is used as input for the inverse method algorithm (the result would be quite similar with all the cutting signal but it would require the use of higher dimension matrix thus higher computation time). The superimposition of simulated (using linear cutting force model) and measured signal is shown on Fig. 3. The identified parameters are summarized in table 1.

Table 1: Identified parameters

| | | | |
|---|---|---|---|
| runout | 4,6 $\mu m$ | $K_t$ | 2997 MPa |
| $K_r$ | 2361 MPa | $K_a$ | 734 MPa |

## Uncertainty management

Cutting force recorded during each revolution of the cutter can be treated as a random signal whose parameters can be identified. For each sample time, a normal distribution was fitted on the recorded force values (x, y and z), each adjustment was achieved on 90 values. The adjustment was performed by using a regression method, based on the median rank estimator to obtain a non-parametric cumulative distribution [14]. The table 2 shows the main results of the fitting procedure. The coefficient of determination $\rho^2$ is used to quantify the quality of the adjustment:

$$\rho^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \overline{y})^2} \tag{3}$$

with $y_i$ the $i^{th}$ observed value, $\overline{y}$ the mean of observed values and $f_i$ the $i^{th}$ modelled value.

Table 2: Results for the normal distribution fitting on the force measurement

| | $F_x$ | $F_y$ | $F_z$ |
|---|---|---|---|
| Mean Standard deviation | 1,956... | 1,807... | 2,428... |
| 95% confidence limit | 3,833... | 3,541... | 4,818... |
| mean $\rho^2$ | 91,74% | 93,49% | 92,36% |

Fig. 4 represents the evolutions of the 95% confidence intervals superimposed over the mean signals. The Fig. 5 shows a comparison of the standard deviation obtained for the three force measurement directions.

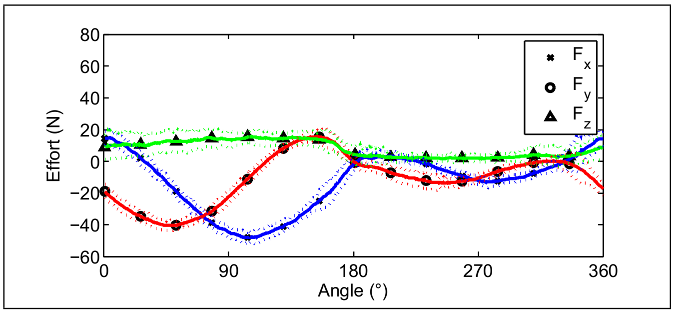

Fig. 4: Evolution of mean force with 95 % confidence interval.

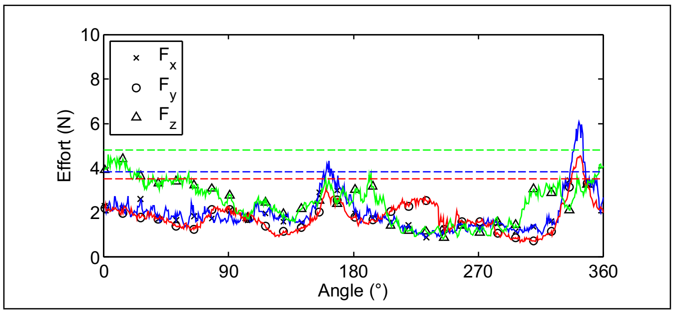

Fig. 5: Standard deviation estimated for each sample time (dashed line is the 95 % confidence treshold).

## Stability of milling operation

The variability of the cutting force signal has been taken into account by adding a random noise on the simulated signal. The estimated mean standard deviations obtained for force signal along the three direction (see table 2) were used to obtain the same type of signal as measured one (Fig. 6).

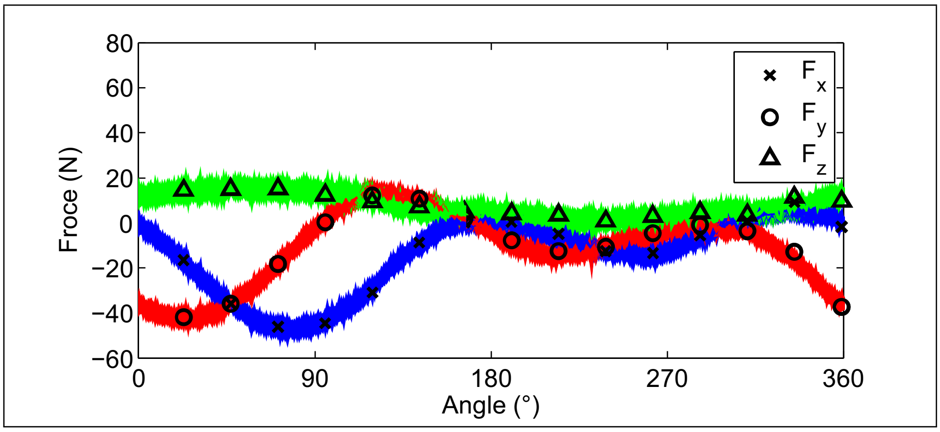

Fig. 6: Simulated signal with random component.

The proposed model has been tested on a testcase of dynamic simulation of milling operation. In order to show the effect of heterogeneity of the cutting force on the stability of the operations, both cutting forces models (mean signal and signal with random component) have been used to predict stability lobes. The proposed system has the dynamic parameters of a micromilling found in [15]. The same tool is used (2 mm diameter, 2 flutes) and the parameters of cutting force model are those identified in table 1. The stability lobes are obtained by performing full dynamic simulation of milling at different spindle speeds and axial depths of cut. The limit depth of cut (which separate stable and unstable regions) is selected as the one showing an increase of 25% of undeformed chip thickness as compared to the rigid case (this method has been proposed in [16]). Stability lobes diagram is shown on Fig. 7.

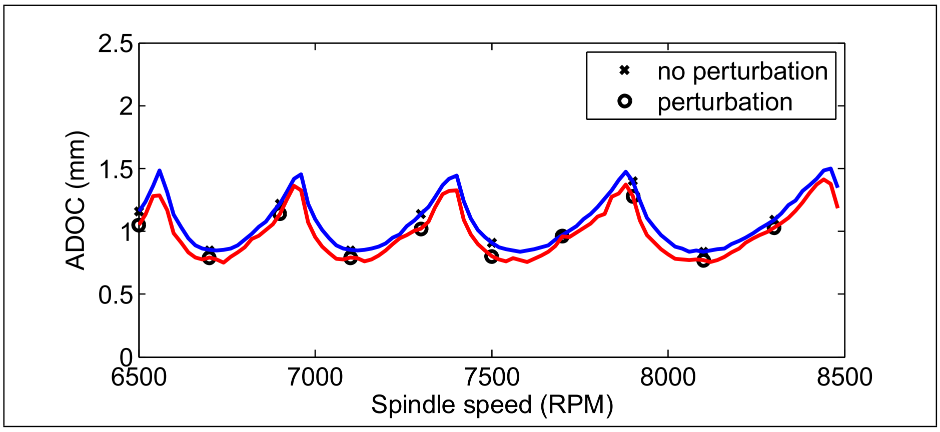

Fig. 7: Comparison between stability lobes obtained with and without taking variability into account.

The comparison of the stability lobes shows a decrease of the stability limits when the perturbation is taken into account. It can be seen that the reduction seems to be more pronounced at the minimum values of the lobes. However, for this first approach, only one set of random values has been used; a more complete analysis would be required for further developments.

## Conclusion and further work

In this paper a generalization of inverse analysis method for cutting forces simulation has been performed. First the measured signal has been used to compute exact spindle speed to establish autocorrelation of the signal along each cutter revolution. Then the mean value has been used to retrieve the best analytical cutting force coefficients in order to reduce optimization time. An analysis of variability of the signal has been performed in order to add the effect of unpredictable variation during machining (such as heterogeneity of the material). Finally, this variable model has been applied on dynamic simulation of milling operation to compute stability lobes.
Further work will consist in a generalization of the procedure in order to extract trends for the simulation of a complete set of experimental tests. Confidence intervals on stability lobes could also be an interesting element to compute in order to add some part of confidence level on the decision.

## References

[1] T. Altan and V. Vazquez. *Annals of the CIRP*, 45/2:599-615, 1997.

[2] C. Brecher, M. Esser, and S. Witt. *CIRP annals - Manufacturing Technology*, 58:588-607, 2009.

[3] A. Attanasio, E. Ceretti, S. Rizzuti, D. Umbrello, and F. Micari. *CIRP Annals - Manufacturing Technology*, 57:61-64, 2008.

[4] D.A. Axinte and R.C. Dewes. In *Metal Cutting and High Speed Machining*, 171-179. Kluwer Academic/ Plenum publishers, 2002.

[5] B. Denkena and F. Hollman. Springer lecture notes in production engineering, 2013.

[6] Y Altintas. Cambridge university press, 2000.

[7] S. Engin and Y. Altintas. *Int. J. Mach. Tools Manuf.*, 41:2213-2231, 2001.

[8] W.A. Kline, R.E. DeVor, and J.R. Lindberg. *Int. J. Mach. Tool Des. Res.*, 22:7-22, 1982.

[9] E. Budak, Y. Altintas, and E. J. A. Armarego. *ASME J. Manuf. Sci. Eng.*, 118:216-224, 1996.

[10] J.H. Ko and D.W. Cho. *Int. J. Adv. Manuf. Techol.*, 26:1211-1221, 2005.

[11] E. Rivière-Lorphèvre and E. Filippi. *Int. J. Adv. Manuf. Technol.*, 45:8:8-15, 2009.

[12] G. Ljustina, R. Larsson, and M. Fagerstrom. *FE in Anal. and Des.*, 80:1-10, 2014.

[13] A. Simoneau, E. Ng, and M.A. Elbestawi. *Annals of the CIRP*, 55:97-102, 2006.

[14] C. Letot and P. Dehombreux. In *Proceedings of the 9th National Congress on Theoretical and Applied Mechanics NCTAM 2012 Brussels (Belgium)*, 2012.

[15] S.M. Afazov, S.M.Ratchev, J.Segal, and A.A.Popov. *Int. J. Mach. Tools Manuf.*, 56:28-38, 2012.

[16] M. L. Campomanes and Y. Altintas. *Trans. ASME*, 125:416-422, Augustus 2003.