

Condition-based maintenance contribution in machining system

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Abstract—The purpose of this article is to compare time based maintenance (TBM) with condition based maintenance (CBM) relative to cutting tools in the process for removing material. We describe the fault detection (FD), method based on the use of the analytical model of the roughness of the work pieces to be machined. This model is established under given cutting conditions and calculated according to the maximum desired roughness. Experimental results are presented for the cutting tool TBM on the one hand, and for the validation of the FD method allowing CBM on the other hand.

Index Terms—Condition-based maintenance, roughness measurements, fault detection.

I. INTRODUCTION

Maintenance strategies in the manufacturing industry are traditionally based on operations of time-based maintenance (TBM), also known as periodic-based maintenance [1], to ensure the availability of the equipment. The instructions of maintenance are given starting from predetermined values of working duration of the pieces of the equipments. These values are generally obtained from average statistics. The TBM can lead either to premature thus useless interventions, or to too late interventions, thus prejudicial to the correct operating of the system. It must be noticed that generally less than 20% of the equipments are used according to their predetermined lifetime in TBM [2].

Condition-based maintenance (CBM) proves to be an adequate answer to avoiding these risks because it refers to the real state of the system, provided it satisfies its implementation requirements [3, 4, 5, 6]. Currently, in order to determine and understand the ongoing physical behavior of machines, and further identify normal and abnormal patterns, various sensors have been developed and adopted to monitor and record information such as temperature, lubricating oil, contaminants, pressure, sound, and vibration [1, 7].

Fault detection (FD) is the first critical step in the CBM design. Developing FD algorithms is a constant aim of many researchers and refers to various principles. One of the main methods is based on the analytical model of the considered process [8, 9]. The model is computed and works parallel to the system. The principle of the model-based fault detection approach consists of a comparison between the measured outputs of the system and the estimated outputs of the model. The same input value is applied to the system and to its model. In fault-free mode, these two outputs are identical (neglecting the noise and modelling errors). The difference between the two values is called residual, $r(t)$, and it should be close to zero. Any occurrence of faults results in a deviation of the measured output and $r(t)$ deviates from zero. A decision logic reduced to a thresholding makes it possible to determine the occurrence of a fault. The threshold is selected to take into account noise levels and modelling uncertainties. This principle of fault detection and diagnosis is used by [10] for two system components of diesel engines (the intake system and the injection system together with the combustion process) and by [11] for both a vehicle lateral dynamics system and an active suspension system. [12] used this principle of detection for the design of an industrial fault tolerant robot. Fault tolerance attempts to equip the system with detection, isolation and accommodation capacities allowing the normal functioning of the equipment despite the occurrence of faults. This concept is detailed in [13].

This contribution from the community of the control engineers is now directly exploitable in the implementation of CBM techniques having the implementation of FD stages in common with fault tolerance.

The study we present aims to optimize the maintenance function of the machine's tools. The proposed approach is to compare between two maintenance strategies for the cutting tool. The first one is TBM used for cutting tools in machining, and based on the determination of the tool life.

The second one is CBM, which is based on the real state of the cutting tool. The specifications in this very context are to produce batches of parts with precise dimensions and surface qualities. As quality control is being related to the roughness of the machined parts [14, 15, 16, 17], we propose to couple these requirements of the specifications to some actions of CBM on the production equipment, knowing that any tool degradation leads to a deterioration of the surface quality, resulting in a variation of its roughness. Thus, we consider this roughness, modelled by a $R(t)$ function, where t is the machining time, as the main indicator of the monitoring stage. In normal operations, the surface roughness depends on several factors [14, 18, 19] and these factors are set up, from the outset, according to the machining process conditions. Roughness modelling is a crucial step of this work and this is the concern of the following section. A case study is then developed in section three and the selected cutting parameters are listed. We use criterion R_a (arithmetic mean roughness) which is the one used by [14, 17, 20], since it reveals details with good accuracy. The fourth section of the paper deals with the tool wear and enables the use of TBM and the last section is devoted to CBM of the cutting tool.

II. ROUGHNESS MODELLING

The surface roughness of the machined parts depends on several factors. Some are systematic such as the geometrical conditions of the cutting tool associated with the cinematic conditions of the generation process. They are modelled by a constant term referred to as generation roughness R_g . Other factors are associated with tool wear and random machining faults, modelled by deterministic or random functions. These last 2 factors are generally added to R_g .

$r(t)$ can be expressed, in a deterministic way, as a linear combination of R_g and of a term ct^m :

$$R(t) = R_g + ct^m \quad (1)$$

The 2 parameters c and m depend on the cutting conditions used during the machining process and are generally obtained by identification techniques.

The random machining errors of the machined workpieces are characterized by a significant dispersion in the experimental results of $R(t)$. It is shown that this measurement dispersion presents a distribution according to the normal law. This distribution is centred, with a null arithmetic mean ($\mu=0$) and a standard deviation σ .

By taking into account these errors, (1) is then limited by a confidence interval:

$$R_g + ct^m - s\sigma \leq R(t) \leq R_g + ct^m + s\sigma \quad (2)$$

Where s is the variable distribution of the normal law.

The roughness variation can then be represented by Fig. 1.

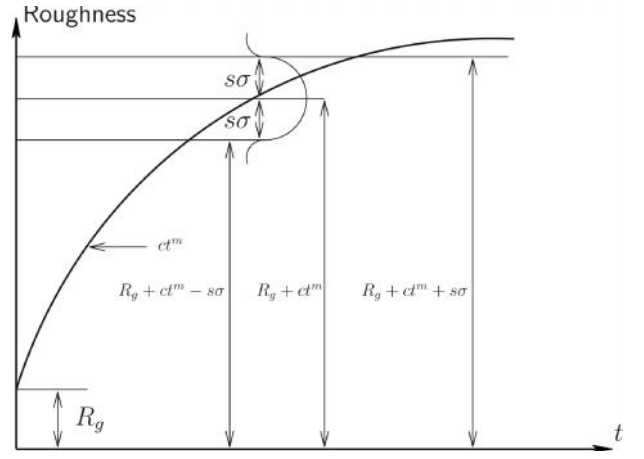


Figure 1. Roughness variation

III. EXPERIMENTAL STUDY

The machining process deals with a tool material couple. The tool is made up of a carbide grade P20, and the material is heat-treated steel grade C38. The dimensions of the workpiece are 100mm in diameter and 150mm in length. Machining consists of a finish turning operation. The maximum roughness imposed by the design drawing is: $R_a = R_M = 4.8\mu m$. In order to satisfy this roughness, preliminary trials were conducted to determine the optimum cutting conditions which are given in table 1.

Table 1. Optimum cutting conditions

Cutting conditions	Values
Cutting speed	250m/min
Feed rate	0.1mm/rev
Depth of cut	0.5mm
Tool radius	0.5mm
Tool clearance angle	6°
Tool rake angle	8°

A. model parameters identification

The roughness model is given by (2), so parameters R_g , c , m and σ must be identified. Measurements have been made with a roughness meter, with a 5.0mm basic length and a 0.8mm cut-off. As these measurements showed a notable dispersion, it was necessary to develop a design of experiments based on 5 series of 10 parts each, according to the statistical measurement techniques in small quantity. Using cutting conditions given in table 1, the results of these measurements are displayed in Fig. 2 and their interpretation makes it possible to break up $R(t)$ in two distinct intervals:

- $0 < t \leq 540s$: $R(t)$ is approximately constant, its value corresponds to R_g .
- $t > 540s$: $R(t)$ follows a variation of type ct^m .

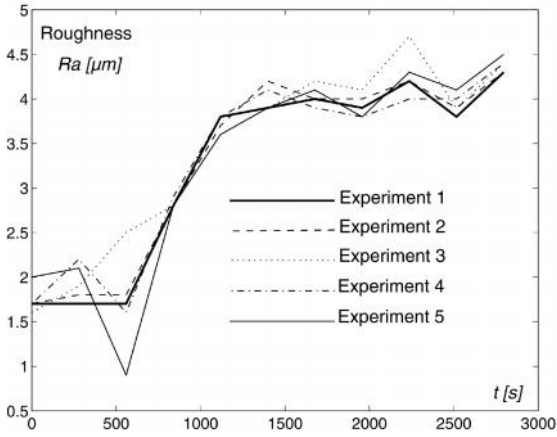


Figure 2. Roughness identification

The data set relative to the 5 curves is processed by the traditional least squares technique and enables us to compute the respective values of c and m . The value of σ is obtained by identifying the greatest standard deviation value of the roughness of all parts tested. These 4 parameters are displayed in table 2.

Table 2. R_g , c , m and σ values

R_g	c	m	σ
$1.79\mu m$	$1 \mu m/s^{0.18}$	0.18/	$0.27\mu m$

IV. PREVENTIVE MAINTENANCE APPLICATION

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A. Tool life time calculation

The normal wear of the cutting tool is generally dealt with by TBM. It is based on the lifetime of the cutting tool, enabling a machining cycle time compatible with the roughness constraints on the parts. This determination of the cutting tool lifetime can be deduced from data relative to a given tool-material couple. The cutting tool lifetime can also be determined in a more precise way when the lifetime model is established.

The maximum roughness value R_M is imposed by the blueprint of the part as the upper limit that cannot be exceeded. The variable distribution of the normal law has a value of $s = 3$ for a confidence interval of 99.7%.

According to the experimental results mentioned above, we can consider that the roughness in the first interval is constant and thus we can carry out a change of coordinates (toR) to ($t'o'R'$) where times τ , τ_g and τ_c are shown in Fig. 3.

From equations (1) and (2), we can deduce:

$$R_g + c\tau_c^m + s\sigma \leq R_M \quad (3)$$

Using the upper limit of (3), one can deduce:

$$R_g + c\tau_c^m + s\sigma = R_M \quad (4)$$

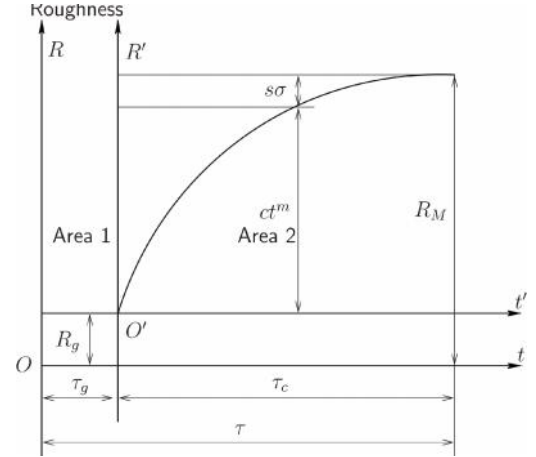


Figure 3. Change of coordinates

then

$$\tau_c = \left(\frac{R_M - R_g - s\sigma}{c} \right)^{\frac{1}{m}} \quad (5)$$

where τ_c represents the machining time cycle relative to the second interval, for which it is necessary to add τ_g to obtain τ , the maximum time of the machining cycle which meets the roughness constraint

$$\tau = \tau_g + \tau_c. \quad (6)$$

$\tau_g \approx 540s$ can be deduced directly from Fig. 1. Equations (5) and (6) linked to the values of table 1 enable us to determine $\tau \approx 2815s$, which is :

$$\tau \approx 47mn \quad (7)$$

The cutting tool lifetime obtained by the model is thus $\tau \approx 47mn$.

V. CONDITION-BASED MAINTENANCE APPLICATION

TBM only takes into account the systematic wear of the tool. But we know that any premature wear of the cutting tool will necessarily result in an increase in the scrap parts. Inevitably, the tool change is not justified and becomes premature if the cutting tool has a longer lifetime. This is our concern in this section..

A. Fault detection scheme

Our approach is a variant of the procedure described in section 1. The values of the cutting speed, feed rate, depth of cut and tool geometry are the inputs applied to the lathe (real system) while the model parameters (R_g, c, m) are the computer inputs, as shown in Fig. 4

The estimated $R(t)$ output is obtained by (1), so residual $r(t)$ is then obtained by:

$$r(t) = R_a(t) - R(t) \quad (8)$$

Let us note that S_H and S_B are respectively high and low thresholds obtained from the experiments and allow us to take into account the noise and modelling errors. We use the extreme confidence level relative to the normal law (99,7%) which makes it possible to write $S_B = -3\sigma$ and $S_H = +3\sigma$.

- if: $r(t) \in [S_B, S_H] \rightarrow$ fault-free mode
- if: $r(t) \notin [S_B, S_H] \rightarrow$ occurrence of a fault

This decision stage, based on the use of fixed thresholds, has the advantage of being easy to implement. This technique, when applied, gives satisfactory results. The thresholding is made possible by the low noise levels in the residual $r(t)$.

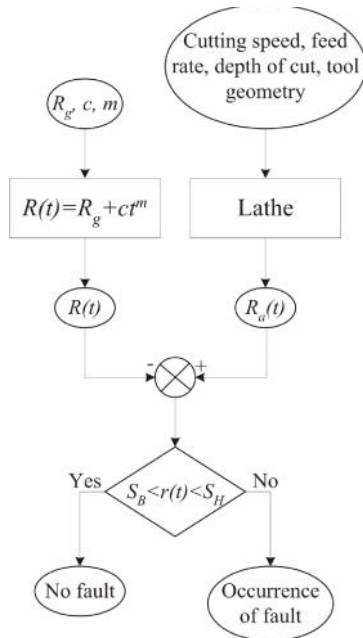


Figure 4. Residual implementation and decision logic

B. Fault detection results

This section deals with the validation of the fault detection algorithms established here above. Cutting tool premature wear w is taken into account. Statistically, in an industrial environment, it is accepted that only one fault can occur at any given time, so that only one fault is considered in the experiment. In the figure giving $r(t)$, two horizontal dotted lines, representing the two values $S_B = -3\sigma = -0.81\mu m$ and $S_H = +3\sigma = +0.81\mu m$ are shown. The maximum roughness

$R_M = 4.8\mu m$ is also shown by a horizontal dotted line on the figure relating to $R_a(t)$.

This fault is introduced at the experimental stage to assess the deterioration of the roughness and to validate the fault detection algorithm.

1) Cutting tool premature wear detection

Cutting tool premature wear is generally due to poor tool quality or poor quality material used in the machined parts. This fault has been simulated by using a worn cutting tool instead of a new one, Fig. 5.



Figure 5. worn cutting tool

At $t \approx 5mn$ $r(t) > S_H$, a fault is detected as shown in Fig. 6. However, despite this fault, $R_a(t) < R_M$ as shown in Fig. 7, the machining can be continued with careful monitoring. The evolution of $R_a(t)$ is shown, from this time, as a dotted line in Fig. 7. The tool lifetime is reached when $R_a(t) > R_M$ with $t \approx 18mn$.

It would be interesting to try to estimate theoretically, from the moment the fault occurs, the remaining time during which the cutting tool is effective with a roughness of less than R_M . This step is known as the prognosis, but obtaining a reliable result in an industrial environment is actually very difficult.

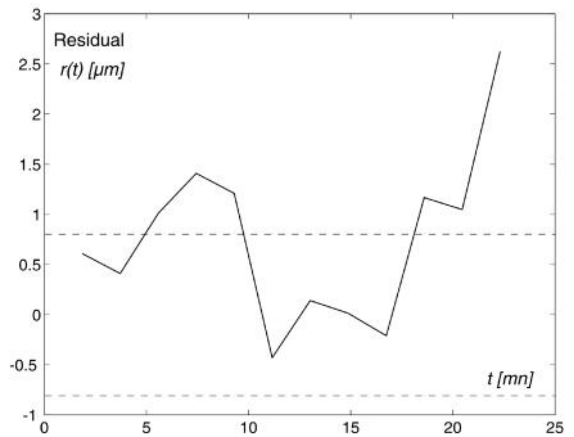


Figure 6. Residual variation with fault W

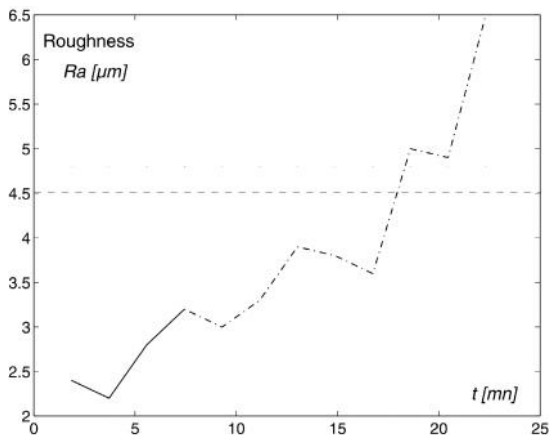


Figure 7. Roughness variation with fault W

VI. CONCLUSION

The purpose of the work is to show the contribution of a condition based maintenance (CBM) compared to a time based maintenance (TBM), particularly in machining. This study makes it possible to completely validate the principle of the FD stage, even if adjustments prove to be surely necessary when the on line system of roughness measurement is adopted. The choice of roughness, as a significant indicator of the cutting tool state, and thus as a central element of the procedure of CBM setting, is all the more judicious as it constitutes the main quality parameter to be validated during the final controls. This consideration can make decision-making concerning the investment of an on line roughness measurement system easier. In the reported case, we have shown that compared to the TBM of the cutting tool, the installation of a CBM makes it possible to avoid approximately 6% scrapped parts, what is of great interest in reducing production costs.

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