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Neural Network Monitoring Strategy of Cutting Tool Wear of Horizontal High Speed Milling

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Abstract**—**The wear of cutting tool degrades the quality of the product in the manufacturing processes. The on line monitoring of the cutting tool wear level is very necessary to prevent the deterioration of the quality of machining. Unfortunately there is not a direct manner to measure the cutting tool wear on line. Consequently we must adopt an indirect method where wear will be estimated from the measurement of one or more physical parameters appearing during the machining process such as the cutting force, the vibrations, or the acoustic emission etc…. In this work, a neural network system is elaborated in order to estimate the flank wear from the cutting force measurement and the cutting conditions.

Keywords**—**Flank wear, cutting forces, high speed milling, signal processing, neural network.

I. Introduction

MILLING is one of the main methods in the manufacturing. Therefore, the detection of tool wear is essential to improve manufacturing quality and to increase productivity. A successful on-line monitoring system for machining operations has the potential to reduce cost, to guarantee consistency of product quality, to improve productivity and to provide a safer environment for the operator. Wear of the cutting tool in milling is a complicated process that requires a reliable technique for monitoring and control of the cutter performance [1], [2].

In most approaches, proposed for the tool wear monitoring area, several parameters can be measured, such as forces, vibrations and acoustic emission, which are directly correlated with tool wear [3]-[7]. Furthermore, these parameters are measured on-line during the machining process. Several studies have focused their effort on the detection of tool breakage. The effect of tool breakage is usually revealed through an abrupt change in the processed measurements showing a value which is in excess of a threshold value.

One of the more common indirect tool Wear monitoring methods is the use of cutting force measurements.

The cutting force signal is considered to be the most suitable signal for tool failure detection in milling operations because the cutting force signal can offer a clear feature for the detection of tool failure/wear.

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Several researchers used the cutting force, to give model for the machining process, or of detect the defects (fracture or wear) of the cutting tool. For this last point the researchers try to find a correlation between the tool wear evolution and the variations of the cutting force parameters. For example, Altintas [2] has shown that the first-order autoregressive time series model AR1 can be used to distinguish the force signal during normal flank wear to that when tool failure occurs. Elbestawi et al. [3] found that certain harmonics of the cutting force increase significantly with flank wear, the number of such sensitive harmonics being related to the number of inserts of the milling cutter and the immersion rate.

Sarhan et al. [4] have shown that the magnitudes of the first harmonics of frequency spectrum increased significantly with increase in tool flank wear, feed per tooth and axial depth of cut.

Therefore, the extraction of the first harmonics from signal spectrum can be used as an indicator to detect the variations of the involved process parameters. Based on ISO 3685-1977, the criterion recommended for end of tool life is when the average width of the flank wear (V_b) exceeds 0.3 mm.

In this context the cutting forces were analyzed in order to determine the relevant parameters which characterize well the cutting tool wear. A series of experiments has been carried out at “Studies and Research Center for cutting Tools, CEROC, LMR, University of Tours, FRANCE” and which constituted the data base of this study.

II. Experimental Setup

An experimental setup was carried out on a horizontal high speed milling machine (PCI Meteor 10). The cutting force was measured by a dynamometer (Kistler 9255B) and the measured force was amplified using a charge amplifier (Kistler 5011). The dynamometer was used to measure the cutting forces in three mutually perpendicular directions: X, Y and Z-axis. During the milling, the Z-axis cutting force component contained little information, but the X and Y-axis cutting forces allowed modeling of the process [5].

The dynamometer was clamped between the workpiece and the table (or pallet), as shown in Fig. 2. In this study, we have used cutter milling type RT130408R-31 with diameter of 25 mm and a workpiece material type 40CrMnMoS8.

The cutting force signal is sampled at frequency of 12 KHz. The milling operations were conducted without applying any coolant, and all cutting tests were performed at the following cutting conditions (Table I), with a single insert.

TABLE I
CUTTING CONDITIONS

S_s	V_c	S_t	a
3647 rpm	280 m/min	0.15 mm/tooth	2 mm

Fig. 1 Illustration of experimental setup

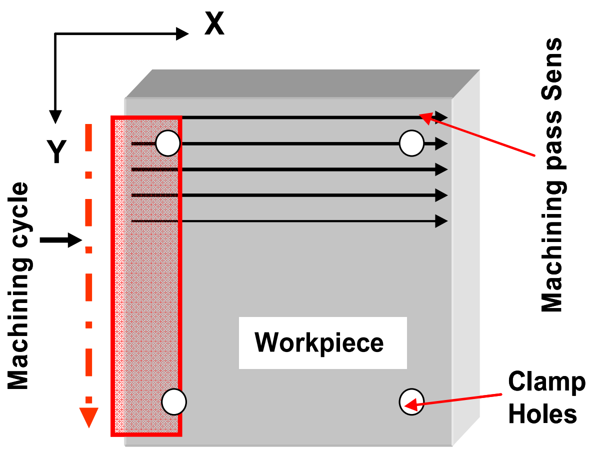

Fig. 2 Machining procedure

The workpiece is machined on its length with catch of measurement at the beginning of race. Fig. 2 illustrates the machining cycle.

III. RESULTS AND DISCUSSION

In the first stage, to have extra-information about the cutting force, we focus on the "force signal part". Windowing the parts of the signal corresponding to the passing of the tool by clamp holes and the tool entry as illustrated in Fig. 3.

Thirty-nine recordings were collected during our experimental test that enabled us to follow the evolution of tool wear during machining time. Fig. 4 shows the evolution of flank wear Vb during the test.

The off-line measurement of Vb and Kt has been done by means of an electronic microscope which is specially conceived to this kind of tasks.

It can be seen in Fig. 4 that flank wear Vb follows the theoretical pattern and presents the three stages of wear, characterized by a change of slope.

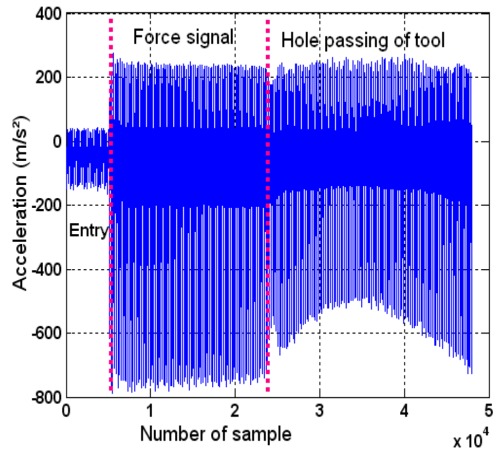

Fig. 3 Temporal Cutting force signal

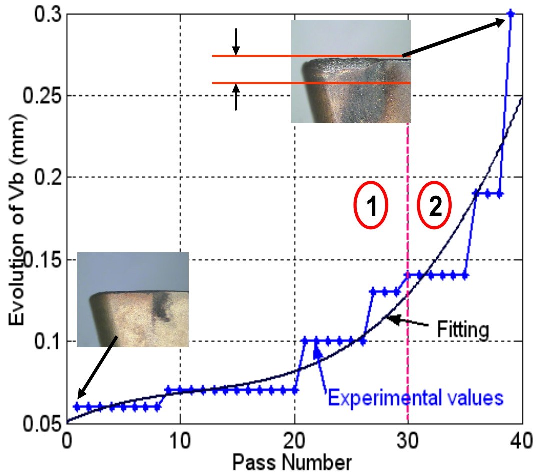

Fig. 4 Evolutions of Flank wear Vb

IV. EXTRACTION OF TOOL WEAR FEATURES BY TEMPORAL AND FREQUENCY ANALYSIS

A. Temporal Analysis

The temporal analysis of cutting force signal is presented in Figs. 5 & 6. Using such statistical parameters as mean, Root Mean Square and variance, it can be observed that the variance values provided more relevant information on the evolution of the milling cutter wear than the values of other parameters [5], [6].

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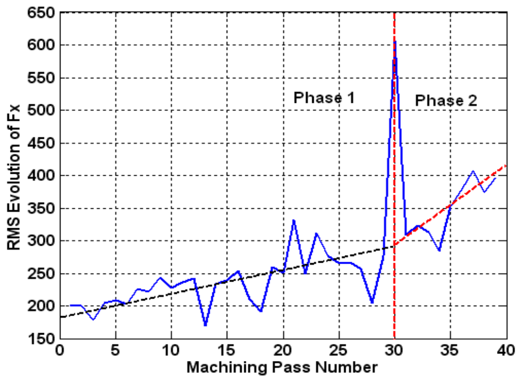

Fig. 5 Evolution of the RMS of F_x

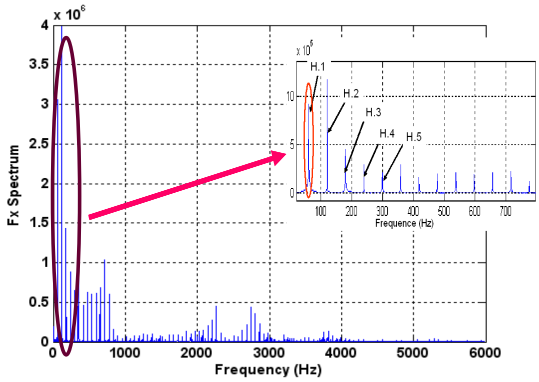

Fig. 7 F_x Spectrum

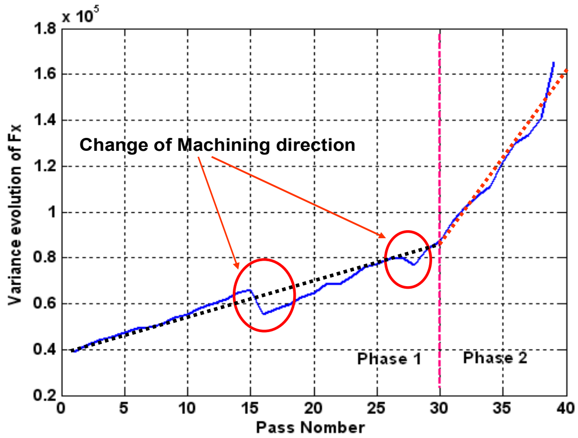

Fig. 6 Evolution of the variance of F_x

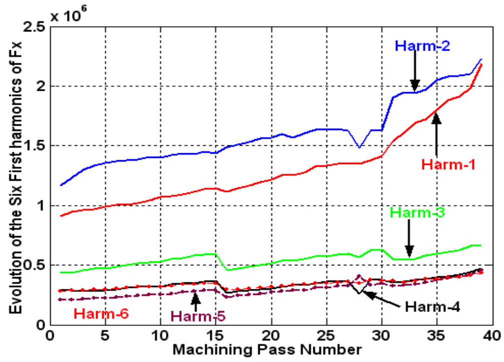

Fig. 8 Evolution of the First Six harmonics of F_x

The variance evolution (Fig. 6) has certain characteristics on the fifteenth (t=300sec) and the thirtieth passes (t=600sec) which represent the change of the machining cycle of the workpiece.

On the other hand, the transition between the second phase (2) and the third phase (3) is characterized by a peak at the thirtieth pass (t=600 sec).

B. Frequencial Analysis

Our study is limited to the evolution of the first six harmonics corresponding to the three cutting forces (radial, axial and resultant) during the machining process, and we observed that the axial force Fx gives best results than the others.

Under a normal cutting condition in the milling process, the dominant frequency components in the spectrum graph are around the tooth passing frequency (TPF), the spindle rotating frequency and their harmonics (Fig. 7). TPF is determined using the following equation:

$$TPF = (S_S.N)/60 \quad (Hz) \tag{1}$$

where Ss is the spindle rotating velocity (rpm), N is the number of teeth of the cutter.

In this study TPF = 60.78 Hz.

In Fig. 11, it can be seen that the magnitudes of certain cutting harmonics increased significantly with flank wear while other harmonics are unaffected.

Furthermore, we have remarked that the first harmonic of the axial force was the most sensitive to the variation of tool wear. In contrast to the variance plot, the harmonic's evolution has certain characteristics only on the fifteenth pass (t=300sec), representing the change of the machining cycle of the workpiece but not on the thirtieth one (t=600sec). Consequently, we deduce that any change of the cutting conditions or the tool performance leads to changes in the amounts of flank wear and then in the significant cutting forces harmonics.

V. Estimate of Flank Wear VB by Neural Network

By definition a neural network is an assembly of elements or nodes "processors" where an under group makes an independent treatment and passes the result to the second under group. The processing capacities of the network are store in the forces (or the weights) of connected inter units which are obtained by an adjustment process (training process). These networks are a type of artificial intelligence which tries to imitate the operation of a human brain. Instead of using a model digital, in which all the operations handle of the zeros and the ones, a neural network proceeds by creating connection between nodes. The organization and the weights determine the outputs. The neural networks can be used to estimate an output from one or more input and a target output [8]-[10].

The generation stage of the NN gives the following results (Figs. 9 and 10). We notice that the estimated output differs much from the measured output Vb, owing to the fact that this result is obtained before the training of the network. The error between Vb measured and the estimated output of the NN are expressed by:

$$Error = \| Vb - real\ output \| \quad (2)$$

The stage of training consists in minimizing this error; for that we fixed the iteration number at 1000, and the error at 0; that give us the results shown by Fig. 10. From this figure, we can notice that the error between the estimated output and the measured output ($V_b$experimental) is practically equal zero.

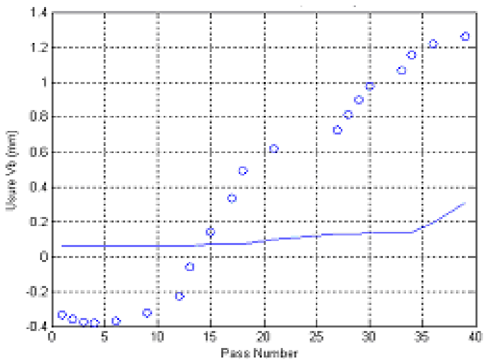

Fig. 9 Output of the NN before the training

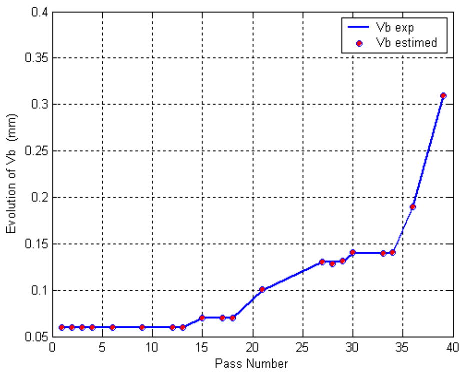

Fig. 10 Output of the NN after the training step

The curves of Figs. 11 and 12 show that the output estimated by the NN tends towards the measured output, consequently, we can conclude that the training of the NN has been well carried out.

In our case, this method makes it possible to estimate wear V_b from the following inputs (K_s, a, C_w, D, V_c, S_t, z, the first harmonic, the variance and the RMS) with a NN (10 neural in input layer-5 neural in hidden layer and one neural in output layer). And if we want to make a classification of cutting tool wear we can draw up a threshold.

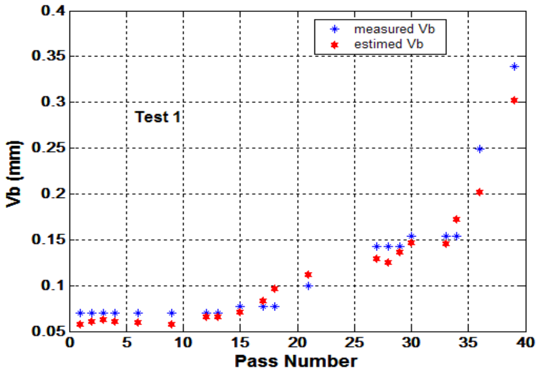

Fig. 11 Test 1 of NN (validation)

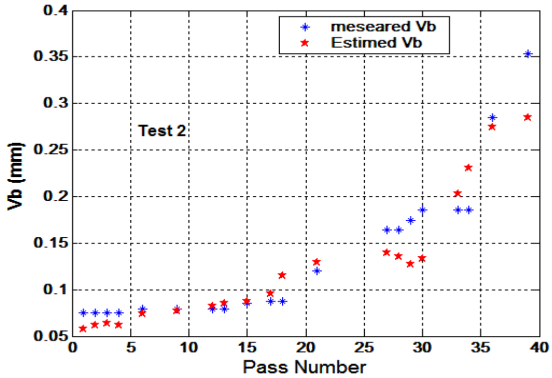

Fig. 12 Test 2 of NN (validation)

VI. Conclusion

This study investigated the use of cutting force signal measurements to improve the on-line tool wear detection and monitoring of coated tools in milling process by developing a predictive method of their wear. To achieve this goal, we have used the cutting force analysis to establish a relationship between the wear evolution and the cutting force variations.

Indeed, we observed some values on the evolution curves of the variance and of the first harmonic that show a change in the nature of the efforts. This change becomes more significant and is characterized by an increase in slope of the evolution curve; it is also directly linked to the transition from the normal phase of the cutting tool wear to the severe phase. We stressed on the influence of the machining cycle on the quality of measurements. This phenomenon should be well taken into account during any measurement of the cutting forces, specially, in horizontal milling.

The first stage was to determine the appropriate indicator revealing of useful information about the cutting tool wear state, it appears that the variance and the first harmonic (spectral) of cutting force according to X-axis provide the relevant information.

An automatic monitoring system of tool wear based on neural networks has been implemented using the cutting condition, the insert type, the values of the variance, and the first harmonic of the cutting force as input vectors to estimate the tool wear. The results obtained are hopeful, it was shown that it is possible to repeat this study on a large scale, by dressing a data base of many inserts. This would make it possible to get knowledge about the tool life for each insert type under various cutting conditions and help to avoid the wasting of inserts because their use time would be optimized. The economic impact of this optimized use would be obviously very significant for industries which use a large quantity of this type of tools.

NOMENCLATURE

A Depth of cut (mm).
Cw The edge force constant (N/mm2).
Fx Axial force (N).
Ks Specific cutting pressure of workpiece material (N/mm2).
St Feed rate per tooth (mm/tooth).
Vb The flank wear width (mm).
Kt The crater wear depth (mm).
Vf Feed speed (m/min).
Vc Cutting speed (m/min).
Ss Spindle speed (rpm).

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