EVALUATION OF SENSOR-BASED CONDITION MONITORING METHODS AS IN-PROCESS TOOL WEAR AND BREAKAGE INDICES – CASE STUDY: DRILLING

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Summary

Today, effective unmanned machining operations and automated manufacturing are unthinkable without tool condition monitoring (TCM). Undoubtedly, the implementation of an adaptable, reliable TCM and its successful employment in industry, emerge as major instigations over the recent years. In this work, a sensor-based approach was deployed for the in-process monitoring and detection of tool wear and breakage in drilling. In particular, four widely reported indirect methods for tool wear monitoring, i.e. vibration signals together with thermal signatures, spindle motor and feed motor current measurements were obtained during numerous drillings, under fixed conditions. The acquired raw data was, then, processed both statistically and in the frequency domain, in order to distinguish the meaningful information. The study of the latter is influential in identifying the trend of specific signals toward tool wear mechanism. The efficiency of this information as a tool wear and/or breakage index is the feature that determines the effectiveness and reliability of a potential indirect TCM approach based on a multisensor integration. The paper concludes with a discussion of both advantages and limitations of this effort, stressing the necessity to develop simple, fast condition monitoring methods which are, generally, less likely to fail.

Key words: tool condition monitoring, vibration signals, thermal signatures, spindle motor current, tool wear, statistical analysis, frequency domain analysis.

1. INTRODUCTION

Manufacturing community is always striving to reduce operating costs while trying to improve product quality and meeting or exceeding customer satisfaction [1]. Focusing on the former intent, production cost reduction is achieved nowadays by using higher cutting speeds and by reducing human resources. As a consequence, over the years, the manufacturing environment has undergone dramatic changes, moving from the stage of conventional machinery to fully automated machining systems. Towards this advance, the oldest and most common "fix it when it breaks" strategy is clearly being replaced by "intelligent" condition monitoring (CM) systems. These systems monitor directly or indirectly the machining conditions utilizing vision-based techniques or sensor-based signals, in order to provide diagnostic/prognostic indices for hard and soft faults; soft faults develop progressively with time creating a gradual degradation of the tool, while, on the other hand, hard faults take place instantaneously causing an abrupt cutoff of the operation (Figure 1). In other words, soft faults lead to a predictable situation, an attribute that makes them appropriate for CM, while hard faults are generally unpredictable and ineligible for this area of research. Consequently, the former type of fault can be used for prediction, while the latter is easier for diagnosis [2].

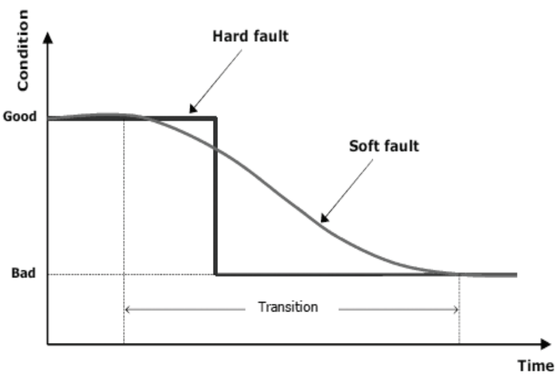

Figure 1: Hard and soft faults, Courtesy of [2]

Specific pivotal components of a machining system, such as the tool, are often related with either soft or hard faults in the form of tool wear and/or breakage. Wear is a loss of material at the cutting lips of drill bit due to physical interaction between the cutting tool and workpiece material [3]. Abrasion, adhesion, diffusion and fatigue are the basic mechanisms that cause wear in cutting tools. Tool wear in drilling is a progressive procedure but it occurs at an accelerated rate once a drill becomes dull. During this procedure, the cutting forces increase, temperature of tool rises, drill point deformation and immediate loss of sharp edges occur. After a certain limit, tool wear can cause catastrophic and sudden failure of the tool without any warning that causes considerable damage to the workpiece and even to the machine tool. This scenario can be illustrated in Figure 2 by classifying the wear stages as initial wear, slight wear (regular stage of wear), moderate wear (micro breakage stage of wear), severe wear (fast wear stage) and worn-out (or tool breakage) in terms of tool life [4].

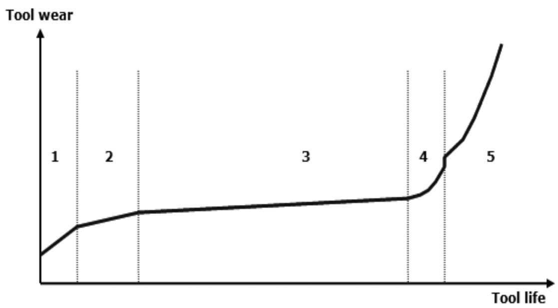

Figure 2: Tool wear evolution: (1) initial wear, (2) slight wear, (3) moderate wear, (4) severe wear and (5) worn-out

In drilling, which is a widely used machining process and represents approximately 40% of all cutting operations performed in industry, the failure of a common twist drill occurs by one of two modes; fracture or chipping and excessive wear. Experiments performed by Thangaraj and Wright [5] indicated that, under normal cutting conditions, failure due to fracture was observed with small size drills (≤ 3 mm diameter), while excessive wear was the dominant failure mode with large size drills (> 3 mm diameter), within a typical drill diameter size range of 1 to 20 mm.

Generally, tool wear influences the quality of the surface finish and the dimensions of the parts that are manufactured, whereas tool failure is a major cause of unplanned interruption in a machining environment. Particularly, for modern machine tools, 20% of the downtime is ascribed to tool failure, resulting in reduced productivity and economic losses [6]. Hence, the reason for acquiring the drill wear state information is to enhance the predictive capability to allow the machine operator to schedule tool change or regrind just in time to avoid underuse or overuse of tools, prevent shutdown of machines due to damage and minimize scrap or rework [1].

Yet, both tool wear and tool breakage are still unsolved primary problems in metal cutting processes, though a considerable amount of research has been done in the literature [3]. Many researchers have looked for variable ways to detect tool wear and, consequently, prevent a tool breakage, but a highly general and reliable on-line tool wear measurement technique has to be developed. Due to the high complexity of drill wear and breakage mechanisms, both mathematical models and numerical methods generally fail to provide a precise description of the relevant dynamics of drilling. As a consequence, the "safe" way to implement a system able to predict and diagnose drill wear and breakage lies upon on-line tool condition monitoring (TCM).

In principle, there are two possible TCM approaches, i.e. direct and indirect methods. Direct tool wear estimation systems are able to measure directly the tool wear via tool images, computer vision, etc. which means that these methods actually measure tool wear as such. Moreover, their application is simple and the reliability is high. However, the automated application of a direct tool wear estimation system is not feasible because the detection system should be able to detect the wear zone and measure it, requiring that either the tool be removed from the machine after a certain period of time or a measuring device be installed on the machine. Consequently, any of these practices would cause downtime and production loss, rendering direct methods either economically or technically inadequate. On the other hand, instead of wear, indirect monitoring methods measure something else, i.e. a parameter, which must be a function of wear [7]. Commonly used parameters in indirect methods are cutting forces, vibration, acoustic emission, current, power and temperature. The main advantage of indirect methods is that they are applied online. Unfortunately, these methods present limited reliability and design complexity due to the unpredictable impact of the wear process to the measured signal. Moreover, the sensor cost is generally high [2].

2. EXPERIMENTS

2.1 Experimental background

This experimental work deals with the use of four common indirect TCM methods in an attempt to evaluate their validity as in-process tool wear and/or breakage indices, during standard drilling processes. Specifically, vibration signals, thermal signatures, spindle motor and feed motor current measurements are obtained and, then, processed in order to extract the meaningful information from the raw data and assess the proclivity of the above parameters toward drilling tool wear.

Vibration is a widely used parameter in indirect TCM. It is logical to expect vibration measurements to react to tool wear; if in a dynamic system such as the machine tool the cutting forces increase, the dynamic response will also increase [8]. Vibration signatures are suggested as reliable, robust and applicable for TCM, in addition to the fact that vibration monitoring techniques present ease of implementation; no modifications to the machine tool or the workpiece are required. Furthermore, vibration signals can be acquired by fewer, easily replaceable and very cost-effective peripheral instruments in contrast to acoustic emissions (AE) for instance. Last but not least, such signals have the quick response time needed to indicate changes for on-line monitoring [9]. Unfortunately, vibration monitoring relates to several limitations. Besides their sensitivity to tool wear, vibrations are highly influenced by the workpiece material, cutting conditions, machine tool structure and machining noise that occurs under real industrial environments.

In the reported literature, tool temperature [10, 11], feed motor current and spindle motor current [12-24] are also widespread parameters for TCM and appear to be potential indices of drill wear. In the same manner as vibration, spindle motor and feed motor current can be related to the dynamics of drilling process, reflecting the amount of power used in the machining process. Although vibration and cutting force sensors are located close to monitored tool, offering hence more representative measurements, it is much easier to acquire the current of the spindle or the feed motor, to monitor the tool condition in a simple, but quite valid, way. In contrast, temperature-based TCM, involving infrared or fiber-optic pyrometers and infrared thermography imagers, is a major challenge due to numerous practical difficulties involved in cutting processes.

2.2 Experimental set-up

Figure 3 presents schematically the experimental setup of this work. As mentioned, vibration, spindle motor current and tool temperature signals were obtained during drilling operations conducted on Yang SMV-1000, a three-axis computer numerical controlled (CNC) vertical-type machining center.

The vibration signals were obtained from Kistler 8702/B25M1, single-axis K-shear accelerometer, mounted on the workpiece longitudinally to the drilling direction, i.e. the Z-axis. The accelerometer has a measuring range of ± 25 g, with a sensitivity of 200 mV/g (± 5%), while its frequency response band ranges from 1 to 8000 Hz. Referring to the spindle motor and the feed motor drives, the related current signals were obtained with two self-powered AC current transducers, LEM type AK 50 C10, with galvanic isolation between the primary (high power) and secondary circuits (electronic circuit). The transducers have a primary nominal input current up to 50 A and give an analogue output signal in the range of 0-10 V DC, with an accuracy of ± 1% and response time < 100 ms. Moreover, non-contact tool temperature measurements were performed with the use of Eurotron's IRtec series Rayomatic 10, a compact digital infrared (IR) temperature transmitter (IR pyrometer) mounted onto the tool bracket, at a distance of d=10 cm from the drill point, with an angle of $\theta=30^o$ from the drill axis. The measuring temperature range of the specific transmitter is from 0 to 600 ^oC, while it offers accuracy of ± 1% rdg and repeatability of ± 0.5% rdg, with a target-to-distance ratio of 25:1. The transmitter was calibrated measuring the known temperature of a specific heat source. Finally, the data from the above four sensors was recorded to a PC, with a sampling rate of 8 KHz, using a National Instruments Cdaq-9172 data acquisition unit and National Instruments LabVIEW software.

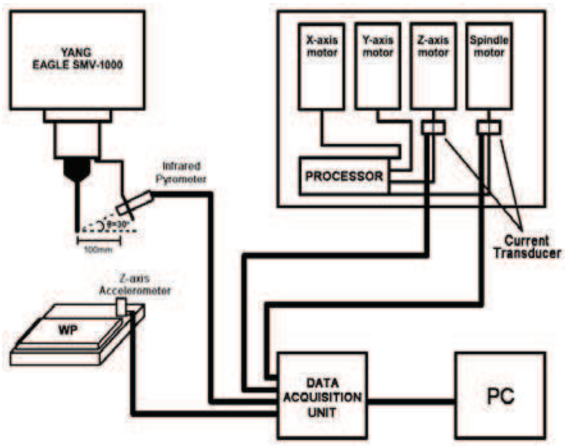

Figure 3: The experimental set-up

The experiments included drilling operations performed by a HSS-Co5% twist drill of 10 mm diameter, under dry conditions, to a number of reinforced C-70 steel workpieces (length=170mm, width=170mm, height= 20mm). Totally 109 bottom holes, of depth=15mm, drilled per each workpiece (Figure 4). The drilling path started from the 1A hole, continued to 1B, 1C and so on, finishing the first line (No. 1) of the workpiece. The process was continuing to the next lines (2 to 11), until the last hole 11K (Figure 5).

The whole process was provided with the use of Missler TopSolid, CAD/CAM software. The selected optimum drilling conditions were S=600 RPM regarding the spindle speed and F=100 mm/min for the feed rate. The duration for a drill was 9 seconds, and for the whole workpiece was estimated around 1800 seconds. The latter includes the "dead" –or rapid movement– time between each drill. One of the aims of this study was to intentionally hasten the drill wear by performing certain drilling operations, in specific workpieces, with "false" conditions (S=800 RPM, F=110 mm/min) between the "normal" sets of drillings, in order to investigate the impact of drill aging, and consequently drill wear, to the monitored parameters. For this scope, exactly after the drilling of hole 11K of the second workpiece, i.e. hole 218, the above "false" cutting conditions were applied for the operation of a whole workpiece; the experiment, then, continued under the aforementioned optimum conditions.

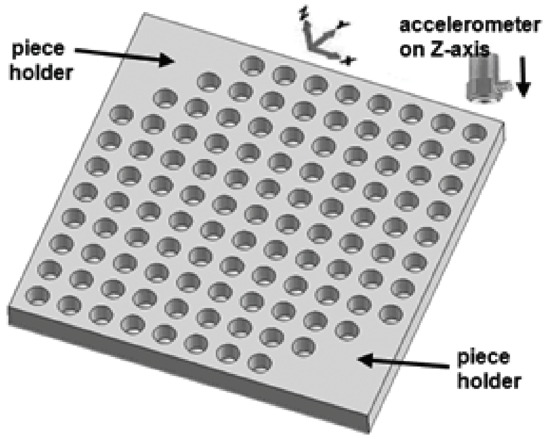

Figure 4: 3-D view of the workpiece model

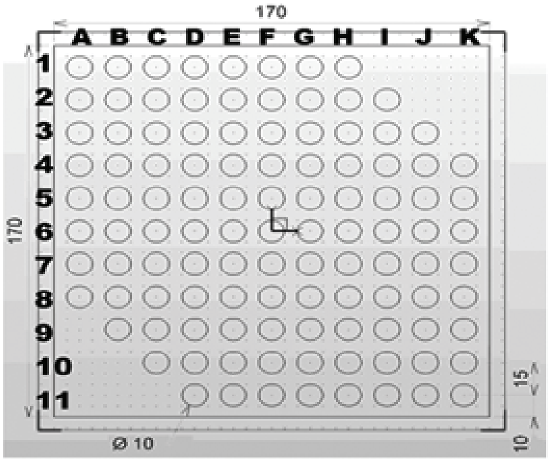

Figure 5: Top view of the workpiece model

3. RESULTS AND DISCUSSION

The previously described cutting conditions and drill aging strategy resulted to a quite significant deterioration of the tool's performance, evident even from the third operated workpiece (WP 3) and, finally, lead to a worn-out state due to which the tool failed and stopped any further drilling on the fourth workpiece (WP 4), after 367 drilled holes.

Figure 6 presents the raw pattern of the obtained Z-axis vibration signals for the time period of specific drillings and the evolution of this raw data through the whole experimental process. As it can be seen in Figure 6, the acquired vibration signals can be characterized as consisting of short oscillatory transients of high, narrow band frequency, occurring randomly within the period required to drill one hole. With the progress of drill wear, the amplitude of these transients starts to increase. Immediately before breakage, these transients resemble those of a resonating system responding to some impulsive excitation in the cutting process at a frequency which is independent of cutting conditions such as feed or speed. By far, the majority of the vibration signals consist of frequency components related to the dynamics of the cutting system.

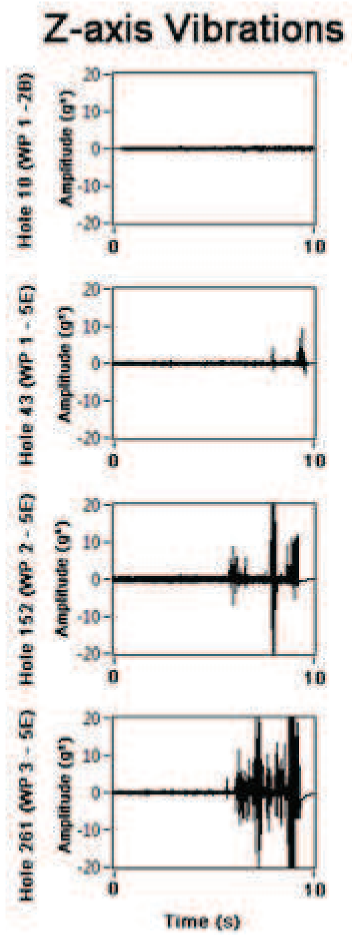

*Figure 6: Raw Z-axis vibration signals for the time period of specific drillings (*g=9.81 m/s²)*

More specifically, there is an indicative "response" of the measured raw signal to the progressively evolving tool wear. The drilling of hole 2B of the first operated workpiece (WP 1), generated vibrations within the range of approximately ± 2 g, in a quite smooth signal pattern; a regular operation of a brand new tool is reflected to this steady-state stage. After 33 drillings, hole 43 gave a vibration signal similar to that of hole 2B of the same workpiece. However, this signal appears to be less smooth due to the presence of numerous spikes across its length, especially at its last part where some vibration spikes reach values near to 10 g. The respective hole 5E of the next operated workpiece (WP 2), i.e. hole 152, gave a vibration signal with a, certainly, rough second half part in which several spikes fluctuate around the region of 10 to 12 g. Moreover, approximately 8 seconds from the start of the specific drilling vibrations approach values near to 25 g, i.e. the measuring limits of the employed accelerometers. Even from this stage of the experiment, the pattern of the generated vibration signal reveals possible slight or moderate tool wear, a remark that can be affirmed observing the next vibration signal, regarding the drilling of hole 5E of the WP 3 (hole 261). Here, the roughness of the signal, in the last 5 seconds, became more intense and more characteristic of a possible severe wear state of the tool. The described dramatic change of the vibration pattern could be considered as a preliminary predictive index of excessive tool wear and, consequently, tool failure which occurred indeed, as mentioned, during a drilling on the next workpiece WP 4.

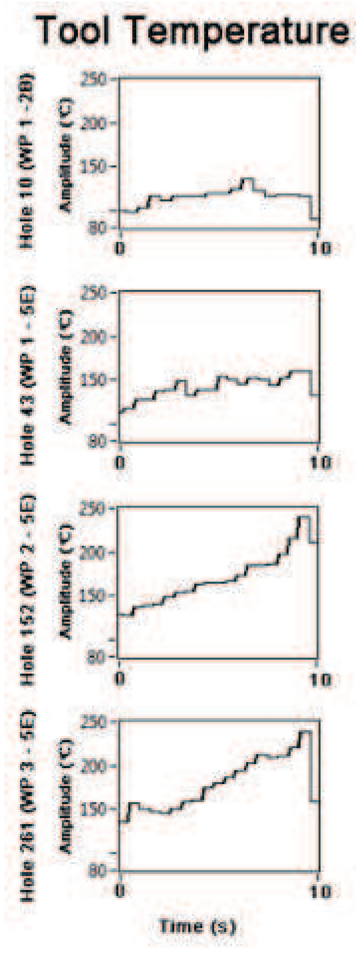

Figure 7: Raw temperature signatures for the time period of specific drillings

In the same way as vibration signals, thermal signatures, in Figure 7, appear to "react" to tool wear. When the tool is brand new (hole 10), its regular operation leaves a temperature offset that fluctuates between 80 and 130 ^{o}C. As the tool continues to drill, the overall temperature level of the signal increases, reaching to a maximum of 150 ^{o}C for hole 43 and 220-240 ^{o}C for holes 152 and 261. It should be noticed that, although the maximum temperatures for holes 152 and 261 seem to be practically equal, the overall level and the average value for hole 261 appears slightly increased in contrast to that of hole 152.

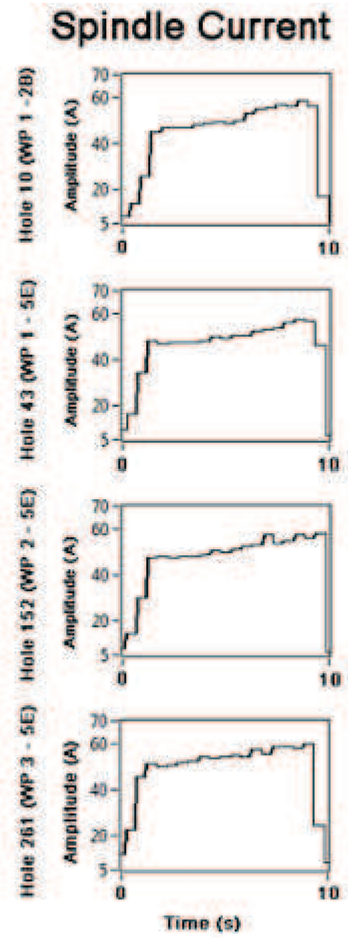

Figure 8: Raw spindle motor current signals for the time period of specific drillings

On the other hand, according to Figure 8, spindle motor current signal, in a raw form, may not be considered as legible tool wear index. Feed motor current showed a raw signal pattern similar to the spindle motor current's one and it is neglected in this analysis. It can be said that, both spindle motor and feed motor current do not "react" to tool wear as dynamically as other parameters, such as vibrations and tool temperature; the obtained raw signals from holes 10, 43, 152 and 269 have similar characteristics and any effort to interpret and correlate them in terms of tool wear is, at least, unreliable. Thus, for these two parameters, further analysis and signal processing are reckoned as necessary.

In order to configure a more in-depth view of the impact of tool wear to the measured parameters, statistical (time domain) and Fast Fourier Transforms (FFT) analyses (frequency domain) were performed. Statistical analysis of the acquired signals included the assessment of mean, average, maximum, variance, kurtosis and RMS values in each signal. Kurtosis and RMS performed significantly well as tool wear indicators but kurtosis proved to be unable to "notify" and obviate tool breakage. Hence, suggestively, Figure 9 shows the chart resulted from the RMS values of the obtained vibration signal and the related best fit curve, through the entire duration of operations to the first three workpieces, i.e. from hole 1 (WP 1 – 1A) to hole 327 (WP 3 – 11K). Both the obvious trend of the RMS values and, mostly, the best fit curve show the expected; vibration measurements react to drill wear, as it has been also noticed from Figure 6. The machine tool is a dynamic system and as the wear of the tool increases, cutting forces increase too and consequently the system's response will also increase. This "interaction" between the tool wear evolvement and vibrations, renders to an exponential curve, as shown in Figure 9.

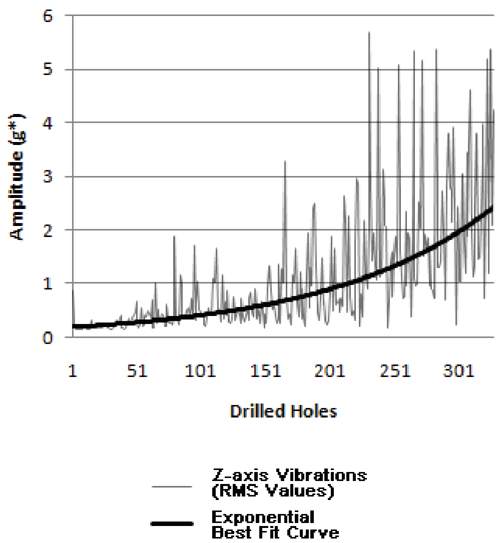

*Figure 9: RMS values of the obtained vibrations and the related best fit curve (*g=9.81 m/s²)*

The corresponding function of the exponential curve is giver from equation (1).

$$v = 0.186 \cdot e^{0.008 \cdot h} \quad (1)$$

where v is the amplitude or the vibration value, in g (vertical acceleration), and h is the number of drilled holes which corresponds to tool use and, consequently, to tool wear. Experientially, in such cases, there is a threshold where the slope of the curve increases in a sensible way that reflect the worn-out state of the tool. For the current cutting conditions, workpiece material and tool structure this threshold is estimated between hole 327 and 340.

In the same way, Figure 10 shows the chart generated from the RMS values of the obtained tool temperature signal (tool thermal signature) and the related best fit curve, for the same duration as Figure 9. As the tool wear increases during the time and the process, the heat balance among the tool, the piece and the chip is unsettled and consequently the cutting edge temperature increases too. As with the RMS vibration values, here, RMS tool temperature values reveal the same substantial interaction between tool wear and tool temperature that is noticed in Figure 7 and can be described by a logarithmic approach, i.e. the best fit curve that corresponds to the function that is given by equation (2).

$$T = 12.45 \cdot \ln(h) + 96.17 \quad (2)$$

where T is the amplitude or the tool temperature (in ^{o}C). The logarithmic form of the above best fit curve can be explained by the fact that, after a prompt increment to the tool's temperature value (transient state), its finite heat capacity decelerates the rise of the temperature within the tool material until a critical "breakdown" in which the tool glows and fails due to excessive wear and/or dissolving.

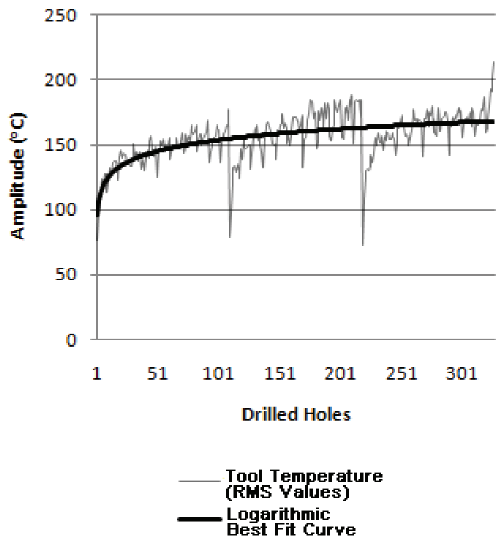

Figure 10: RMS values of the measured tool temperature and the related best fit curve

Figure 11 presents the chart resulted from the RMS values of the obtained spindle motor current signal and the related best fit curve, from drilled hole 1 to 327. There is a slight, but evident, trend of the RMS values of spindle motor current toward the number of drilled holes and, consequently the tool wear. This trend can be described by the linear best fit curve in the same figure and mathematically represented by equation (3).

$$I_s = 0.013 \cdot h + 46.5 \quad (3)$$

where I_s is the amplitude or the spindle motor current (in A). This linear function reflects the slowly evolving increment to the spindle current's values as the tool passes from the initial wear state to moderate, severe and, finally excessive wear state (worn-out). In other words, when the cutting tool is almost new, it drills under optimum performance consuming the less possible spindle motor power/current. As the tool continues drilling, its cutting edge cannot perform in an optimum way and, therefore, the tool needs more power; as a result, the spindle motor current consumption increases progressively with the tool wear.

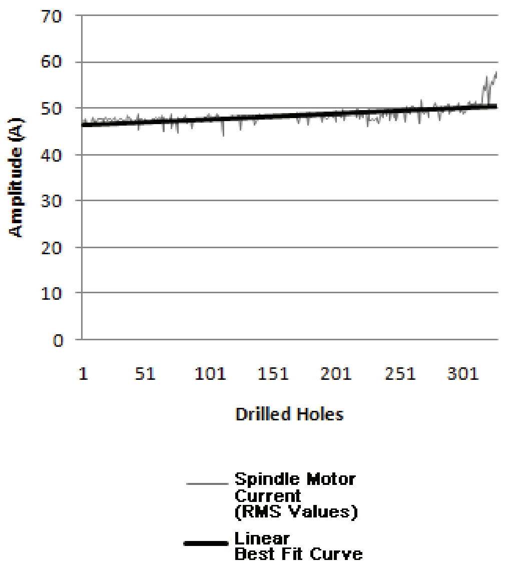

Figure 11: RMS values of the measured spindle motor and the related best fit curve

During the analysis of the obtained signals that were evaluated in this work, the feed motor current proved to be the less representative parameter for tool wear detection. As it has been already noticed, raw data showed that feed current presents an almost stable behaviour against progressive tool wear, a fact that is confirmed by the statistical analysis, in time domain, of this signal. Figure 12 shows the evolution of the RMS values of the obtained feed motor current signal and the related best fit curve, for the operation of the first three workpieces. It is clear that, the major part of these RMS values ranges from 1 to 3 A with several, but random, spikes across the entire signal, that reach values from 4 to 5 A. Similarly to the spindle motor current case, the best fit curve for the feed current is linear.

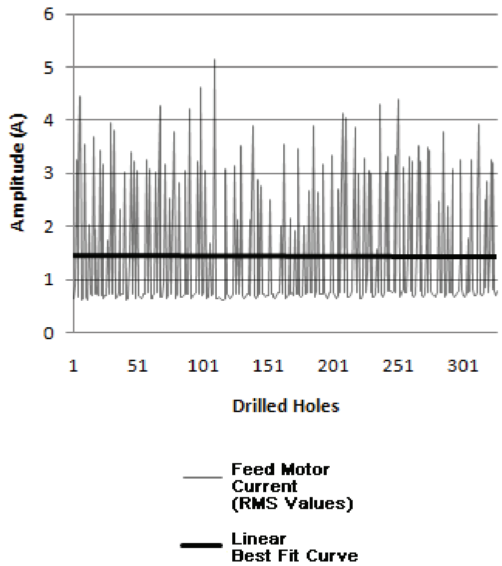

Figure 12: RMS values of the measured feed motor and the related best fit curve

However the feed motor current's amplitude curve of Figure 12 remains constantly to the value of approximately 1.5 A and, consequently, does not indicate any interaction between the tool wear and the feed motor current. The relative linear function is given by equation (4):

$$I_f = -7 \cdot 10^{-5} \cdot h + 1.44 \qquad (4)$$

where I_f is the amplitude or the feed motor current (in A). As for spindle motor current, the above best fit curve is described by a linear function, in the form of $y = a \cdot x + b$. In this case, the slope of the curve is $a = -7 \cdot 10^{-5}$ and, thus, it can be neglected resulting to a nearly constant feed motor current $I_f = 1.44$, independent from tool wear.

In addition to statistical analysis, Fast Fourier Transforms from time domain to frequency domain is also a widely reported signal processing technique, for such indirect methods of tool wear monitoring. FFT is an efficient algorithm to compute the discrete Fourier transform (DFT) and its inverse. In this work, FFT analysis was applied to the raw data of the obtained signals, using a 3rd order Chebyshev bandpass filter with cutoff frequency n_c=4 KHz. Figure 13 presents the results of this analysis to the signals of vibration for holes 10, 43, 152 and 261. The presented power spectral density (PSD) of each signal is in fact the square of the FFT (magnitude).

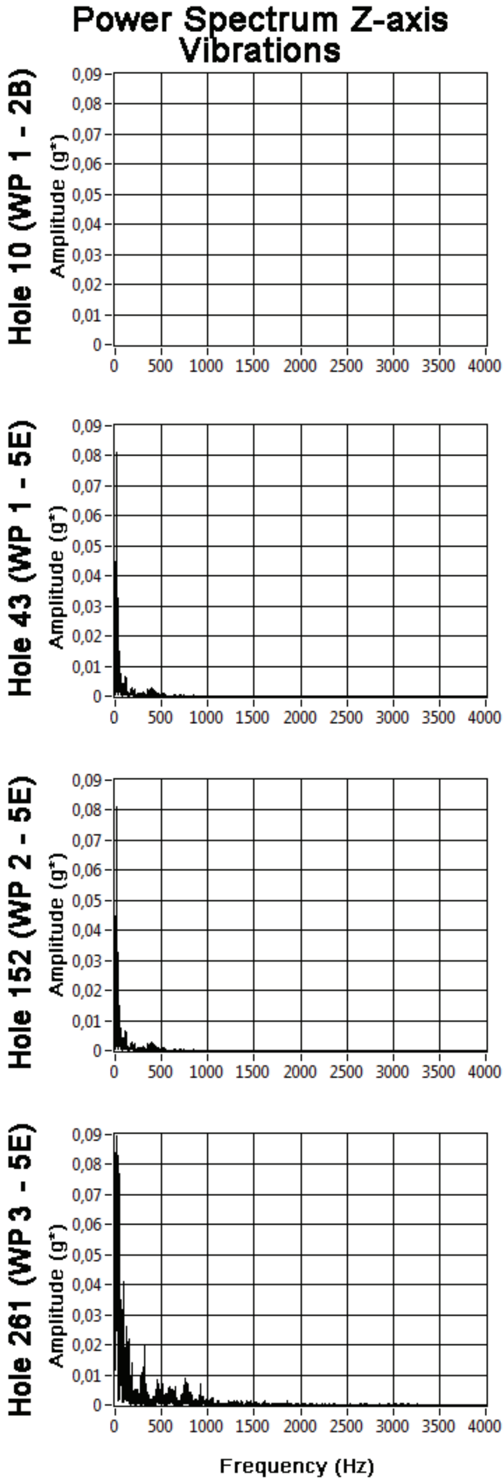

*Figure 13: FFT analysis of the obtained vibration signals (*g=9.81 m/s^2)*

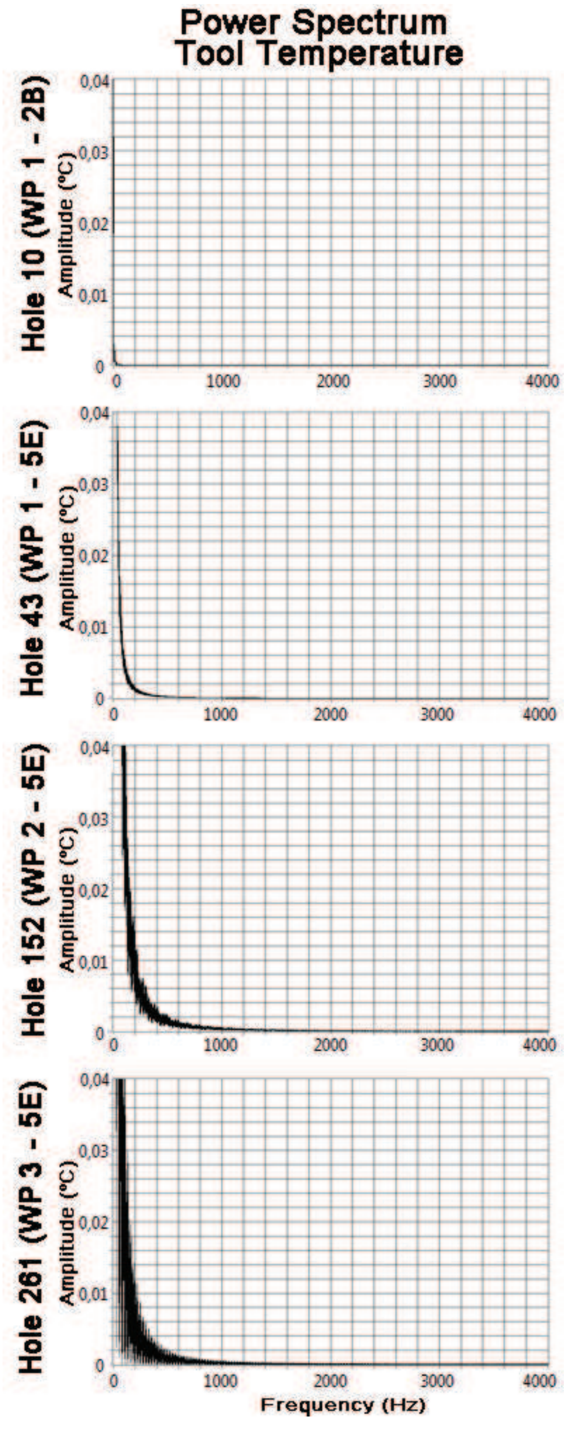

Figure 14: FFT analysis of the obtained tool temperature signatures

As other researchers have already mentioned [25], different combinations of cutting conditions result in different patterns and amounts of drill wear. The various drill wear patterns may change the resulting vibration signatures in the frequency domain. Therefore, it is important to investigate the effect of each type of wear on the vibration power spectra generated during drilling process. This is accomplished by performing "controlled" wear experiments. In the experiments of the current work, due to lack of "controlled" aging mechanism, mainly two types of wear were experimentally induced on the drill, and the resulting vibration and temperature spectra were evaluated. These types of wear are the outer corner wear and the flank wear according to Kanai and Kanda [26] classification. According to the same researchers, the dominant types of wear which result in drill failure and breakage are: chisel wear, outer corner wear, flank wear and margin wear.

Figure 13 indicates qualitively the increment of the vibration signal's power amplitude, in the frequency range of 1.0-2.5 KHz, gradually with the progress of wear. An almost identical trend is seen in the temperature related signal (Figure 14). In general, the vibration signals measured in the Z-axis direction are predominantly affected by corner wear and margin wear. Flank wear and chisel wear have similar, but lesser effects on the vibration spectra, as other researchers have mentioned [27]. The results show, undoubtedly, that both vibration and temperature spectra can be used to identify worn drills.

Figures 15 and 16 show, in an unambiguous way, the impact of tool wear to the tool edge's surface morphology. These images, obtained by a microscope lens, confirm the observed and previously discussed progressive tool wear that was indicated, mainly, by both vibration signals and tool temperature signatures and, secondly, by the spindle motor current measurements.

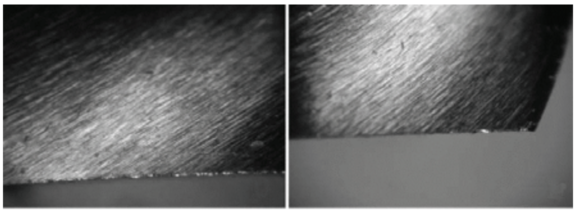

Figure 15: Microscope-based view of the performed tool's edge before the experiment

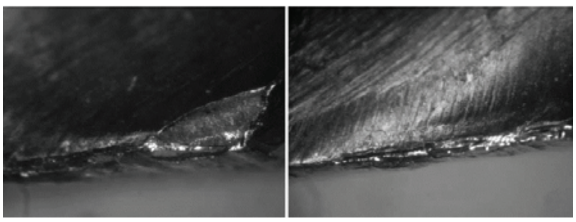

Figure 16: Microscope-based view of the performed tool's edge after 367 drills (excessive wear)

4. SUMMARY

The presented experimental study investigated the efficiency of vibration signals, tool temperature signatures, spindle motor current and feed motor current as in-process tool wear and/or breakage indices in drilling.

A brand new drilling tool was employed to perform several drills under selected "normal" and "false" conditions in order to achieve a significant level of wear. During these operations, an accelerometer, an IR temperature transmitter (infrared pyrometer) and two current transducers were used to obtain the generated signals of vibration, tool temperature and spindle/feed currents respectively. Statistical parameters in time domain, such as RMS, and FFT analysis in frequency domain were used to extract the meaningful information from the raw data.

The results of this work indicated a significant interaction between specific signals and the dynamics of the drilling process, i.e. the slowly evolving tool wear. Even from a quick view to the raw signals, vibrations and tool temperature prove their supremacy as quite reliable and robust tool wear prognostic indices. Further signal processing of these two parameters clearly confirms their reaction to tool wear, verifying Figure 2. Although, it can be said that, tool temperature acquisition was proved to be more suitable for implementation in a real industrial environment, in contrast to vibration monitoring techniques, which are strongly dependent on noise, cutting conditions and specific, only, tool wear types. With regard to spindle motor current, it was noticed that the acquired raw data was inadequate to indicate a clear correlation between this parameter and the tool wear. Nevertheless, statistical processing helped to extract a quite crescive curve reflecting a linear relation between spindle motor current and tool wear. On the other hand, feed motor current was found as contraindicative parameter in this study. Neither raw data analysis, statistical parameters nor FFT analysis showed that tool wear could induce the characteristics of feed motor current signal.

In conclusion, generally speaking, the simpler a TCM system is, the less likely it is to fail. Reliability was rated as being the most important concern by those actually using some form of TCM. Thus, it is obviously vital to minimize the complexity of any future TCM system [6]. Further ambition of the current research team is to:

- Develop practical vibration monitoring techniques which are sensitive to tool conditions but relatively insensitive to cutting conditions and sensor location.
- Assess the applicability of infrared thermography, with the use of portable thermal imagers, to tool temperature data acquisition.
- Prepare and implement several precise and "controlled" rapid tool aging strategies.
- Investigate same or similar sensor-based methods for in-process tool wear/breakage monitoring in other cutting operations, e.g. turning or milling.
- Enrich the presented monitoring system with a fuzzy logic and neural network based classification tool.

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