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Generalizable Tool-Wear Monitoring in Brownfield CNC Milling via Time, Frequency, and Time-Frequency Vibration Features

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Abstract: ***The paper proposes a practical, scalable, and non-intrusive system for the automatic detection of tool wear under real industrial conditions that does not require process metadata (e.g., spindle speed, feed rate) or specialised equipment. The proposed method is based solely on the analysis of triaxial vibration signals and combines multiple signal-processing methods (time, frequency, and time-frequency) to enable deeper analysis. Various time-domain features, such as RMS, standard deviation, kurtosis, and crest factor, are combined with spectral analysis via Welch power spectral density (PSD) estimation and the continuous wavelet transform (CWT) for time-frequency analysis. To make features comparable across machines and operating conditions, the features are combined using median statistics and normalised relative to the median (Δ%). Experimental validation was performed with multiple machines and measurement axes on real industrial datasets that were heavily imbalanced. It was shown that there is a direct and consistent correlation between the condition of worn tools and the overall increase in tool vibration energy, as evidenced by significantly higher RMS and standard deviation values. On the other hand, higher-order statistical measures, such as kurtosis and crest factor, were less consistent when used alone due to their sensitivity to operational variability. Frequency domain analysis showed that the wear of the tool could not only be described by a general rise in energy, but also by the significant increase of certain frequency components in the spectrum. Most notably, the peaks centred at 200 Hz were found to be significantly raised, along with their harmonics at around 600 Hz and 800 Hz, when the tool was worn, and this was true for all the axes of the measurements. These frequencies can thus be considered reliable and repeatable indicators of tool wear. The continuous wavelet transforms (CWT), a complementary method to time-localised time-frequency representations, confirmed the results and, notably, revealed that the signal's high-energy bursts are time-recurrent and running; thus, they can be seen as a series of bright spots closely packed in time in the scalogram. The strength of the proposal is its rational and transparent integration of several well-known signal-processing methods into a single, coherent concept that encompasses the full spectrum of changes, from the global increase in vibration energy to the localised, frequency-specific excitations that are the hallmark of wear progression. By combining global energy indicators with spectral and time frequency features, the approach enhances diagnostic reliability while improving physical understanding of tool-wear mechanisms. It is robust, practical, and readily transferable, offering strong potential for scalable predictive maintenance applications in machining environments.***

Keywords*: *Condition Monitoring, Continuous Wavelet Transform, Power Spectral Density, Tool Wear.

Nomenclature:
PSD: Power Spectral Density
CWT: Continuous Wavelet Transform
MODWT: Maximal Overlap Discrete Wavelet Transform

I. INTRODUCTION

Predictive maintenance is increasingly regarded as the primary lever for reducing unplanned downtime and increasing productivity in newly constructed production shops (brownfield environments). However, introducing such systems in already operational industrial sites is a highly complex task, largely due to the large scale, variety, and complexity of the installed equipment. These plants often contain several legacy machines that are minimally instrumented and lack built-in connectivity, making data acquisition challenging, if not impossible, unless one resorts to invasive modifications. Therefore, non-intrusive condition-monitoring solutions that enable the current set of machines to be used without disrupting factory operations are necessary [1]. To this end, we aim to automatically evaluate the health of a process or piece of equipment (GOOD/BAD classification) based solely on triaxial vibration signals. Most standard methods use process metadata (e.g., spindle speed, feed rate, number of teeth) to facilitate diagnosis, whereas our objective is to eliminate such dependence. Traditional vibration-based techniques often combine the effects of rotational speed, making their features highly sensitive to changes in speed [2]. This drawback of the universality of monitoring systems often requires practitioners to either measure or know the cutting parameters to interpret vibration data correctly. To date, only a few papers have thoroughly addressed state diagnosis solely from vibrations, without operational parameters, even though this approach could offer significant advantages for the flexibility and ease of deploying predictive maintenance at large.

Indeed, to address the issue, we develop a reproducible monitoring pipeline based on robust, interpretable vibration indicators. We rely on several simple domain metrics (RMS, standard deviation, crest factor, kurtosis) that are effective for mechanical anomaly detection, as reported in numerous studies [2]. At the same time, we conduct a thorough

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spectral analysis by estimating the power spectral density (PSD) using Welch's method (Hann window), thereby enabling precise characterisation of the frequency content of each axis. To enable fair comparisons across machines and axes, the extracted indicators are transformed into relative changes (%) relative to the reference condition. In addition to highlighting substantial deviations, this procedure also reduces the effect of machine-specific absolute vibration levels. Ultimately, the median of the measurements is computed, a robust method that limits the extent to which outliers and short-lived transients affect the final diagnosis. The method incorporates the time frequency aspect via the Continuous Wavelet Transform (CWT), which gives a combined view of changes in vibration energy over time and frequency. This type of depiction can aid in identifying characteristic frequency signatures of early-stage defects or wear, even under non-stationary operating conditions.

Each methodological block is well established in the literature; however, the main contribution of this paper is its disciplined integration into a coherent, lightweight architecture capable of edge-to-cloud deployment. The process is unfamiliar to the pipeline, which is a distinct point from the rotation, synchronised order, and analysis approaches. Yet this model can also withstand the gradual drift of the machine, operational variability, and strong class imbalance in real datasets (where degraded states are very rare in industrial operations). "Explainability" is a pivotal point: each selected metric has a direct physical interpretation, thereby making decisions traceable and supporting the operator's confidence. As a secondary step, more advanced AI modules (e.g., autoencoders, convolutional neural networks) may be integrated to further enhance detection without requiring the solution to rely on black-box models from the outset. To relate this contribution to current achievements, we first explain vibration-based condition monitoring, beginning with time-domain indicators and progressing to frequency-domain analyses based on the power spectral density (PSD). We then explain the major constraints of these methods in the rapidly changing industrial environment, including variability in speed, noise, and long-term drift, which make the use of absolute thresholds very difficult and thus render cross-machine comparisons unreliable. In the end, we synthesise the contributions of time–frequency approaches and robust normalisation and aggregation strategies, which together form the methodological backbone of the proposed pipeline.

Vibration-based condition monitoring is generally considered a key element of predictive maintenance, primarily because it is non-intrusive, relatively easy to deploy, and sensitive to a broad range of mechanical faults [3]. Since the pioneering work on vibration diagnostics, acceleration signals have been the primary means of identifying phenomena such as imbalance, bearing defects, excessive clearance, structural resonances, and even machining instabilities such as chatter [3, 4]. In the case of tool wear monitoring, vibration is often a preferred indirect indicator: the wearing down of the cutting-edge results in a change of tool-workpiece interaction that, in turn, influences the dynamic response of the tool-machine system and, finally, its vibration signature [5].

In the past, time-domain analysis has been heavily dependent on the extraction of simple statistical indicators such as RMS, standard deviation, peak amplitude, crest factor (peak-to-RMS), and kurtosis [3]. These features essentially reduce the overall vibration behaviour to a few scalar values that remain highly intuitive to practitioners. A gradual increase in RMS or standard deviation is generally interpreted as an increase in vibration energy, likely due to mechanical degradation or increasing tool wear [6]. In the same vein, high kurtosis or crest factor values are usually viewed as evidence of impulsive shocks, which might indicate localised defects such as chipping of the tool or damage to the bearing [3]. In the factory, these measures are generally compared against fixed or adaptive thresholds to determine when to sound maintenance alarms. There are significant advantages to this approach: it is straightforward, computationally efficient, and readily understandable to operators [6]. On the other hand, the research identifies significant drawbacks. Certain indicators do not exhibit consistent wear-related trends, and their responses are highly condition- and defect-dependent [6]. For example, kurtosis values may decrease as degradation becomes more widespread and the signal spreads over a wider band, thereby complicating direct interpretation of this measure.

As a result, while time-domain analysis remains a necessary starting point, it is often insufficient for early and reliable wear detection in complex industrial settings. To refine the diagnosis, frequency-domain analysis is widely used as a complement to time features. The FFT and the power spectral density (PSD), often estimated using Welch's method, help identify dominant frequency components and connect spectral peaks to physical mechanisms [3]. In machining, increases in certain frequency bands or harmonic components have been associated with tool-wear progression, chatter onset, or resonance effects in the tool–machine structure [4], [7].

Compared with purely time-based indicators, spectral analysis can be more informative, as it enables the association of characteristic frequencies with fault modes [7]. However, it usually requires that the signal be approximately stationary over the analysis period. In machining, vibration signals are often non-stationary due to changes in speed, transient phases (start-up, tool engagement), and variations in the cutting process [8]. Thus, the FFT yields a time-averaged picture that can obscure short or intermittent events associated with early-stage defects. This is one of the main reasons why time and frequency methods have been popular. Time frequency methods such as STFT, CWT, and WPT have been introduced to address the limitations of traditional spectral methods in the case of non-stationary signals [9], [10]. Among these, the CWT has gained popularity in vibration diagnostics because it provides a multi-resolution representation, thereby enabling good time localisation at high frequencies and good frequency resolution at low frequencies [10]. This feature is especially advantageous for detecting transients and intermittent phenomena, which are characteristics of machining signals.

In wave-based signal processing, separating noise and wear The reported effects are a key advantage over a global FFT in many studies [11]. To cite

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an example, mechanical tool wear monitoring nowadays uses multiresolution wavelet decomposition, e. g., Maximal Overlap Discrete Wavelet Transform (MODWT) to recondition raw vibration or cutting signals before the subsequent analysis or machine learning, thereby enabling more efficient extraction of wear, related components from noisy, real machining data [12]. Besides that, time-frequency hybrid advanced methods combining wavelet constructs with other adaptive transforms have been suggested to handle the complex, transient character of machining dynamics. A chatter detection scheme, for instance, has recently been put together using wavelet-based synchrosqueezing and Hilbert-Huang Transform, offering a high-resolution time-frequency representation that can reveal non-stationary features like chatter and other transient instabilities [13]. Moreover, a wear state recognition approach that utilises features extracted from wavelet subbands, which are energy or statistical-based, and then applies classification algorithms, has also yielded excellent results [11], [14].

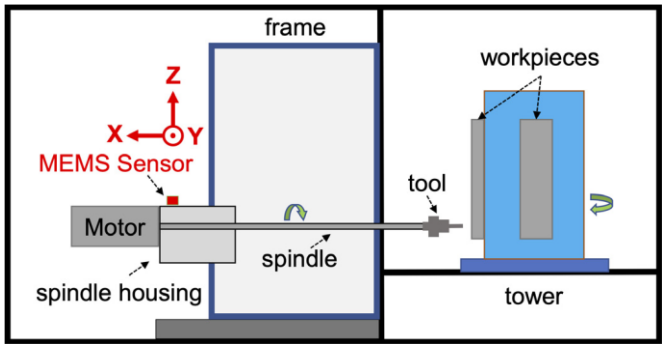
Nonetheless, despite their effectiveness, such methods typically face practical industry challenges: increased algorithmic complexity, sensitivity to fine-tuning parameters (wavelet type, decomposition level, band selection), and dependence on the learning pipeline, which is not always easy to interpret. These issues are even more relevant in brownfield settings, where simplicity, robustness, and traceability are typically non-negotiable requirements. One major challenge in machining diagnostics is that vibration signals are highly sensitive to cutting parameters. A change in spindle speed, feed rate or load can raise or lower vibration levels to a greater extent than the wear itself [15]. Thus, to address this, practitioners frequently resort to order tracking or speed-based normalisation techniques [15]. Nevertheless, these approaches typically require additional sensing (e.g., a tachometer) or a dedicated machine, as well as specific calibration, thereby increasing cost and deployment complexity. The latest trends, e.g., unsupervised learning and domain adaptation, aim to discover defect signatures that remain valid across contexts and thus to generalise them; however, they require large datasets and may produce models that are difficult for end users to justify.

The approach presented in this work takes a deliberately pragmatic, deployment-oriented path within the given framework. Rather than forcibly extracting cutting-parameter effects through additional measurements or extensive modelling, it tracks the relative fluctuation (%) of vibration features relative to an adaptive baseline. The above strategy can offset the slow regime and induced drift, thereby enabling detection of abnormal changes in the vibration pattern, without recourse to process metadata. The method, by synergising interpretable time, domain features, focusing on spectral components, and tapping wavelet, based time frequency analysis, exploits the complementarity of these domains. At the same time, the overall architecture remains simple and explainable. The novelty thus lies not in the invention of a new mathematical instrument, but in a single, firm, and elegant fusion of known methods, illustrated on tri-axial vibration data from typical industrial scenarios, without machine-specific calibration. The objective is a realistic compromise between wear, sensitivity, applicability across machines, and industrial acceptability [9].

II. METHODOLOGY

A. Sensor and Mounting

The data used in this work come from the reference study in [16]. In that paper, the authors use an indirect sensing setup by mounting tri-axial Bosch CISS accelerometers on the rear end of the spindle housing. Data is collected on several 4-axis horizontal CNC machining centres during real production of aluminium workpieces (Fig. 1). This rear mounting location is well-suited for brownfield retrofitting because it stays away from the harsh machining zone—coolant and chips—while preserving a constant distance to the tool centre point. In addition, the accelerometer's three axes are naturally aligned with the machine's linear motion axes (X–Y–Z), which improves the physical interpretability of the measured vibration signals. While some studies mount sensors directly in the machining area, the rear spindle-housing position remains less exposed to extreme conditions and therefore more practical for industrial deployment. [16]. The figure below illustrates the configuration and the measured axis orientation:



[Fig.1: Experimental Setup Schematic: 4-axis Machining Centre with an Integrated Sensor [16]]

B. Sampling Frequency

Vibration signals are acquired at 2 kHz. The most informative content for machining typically lies in the ~75 Hz to 1 kHz band, where spindle order-related components and their harmonics are expected to appear. Under the Nyquist–Shannon sampling theorem, a 2 kHz sampling rate is therefore sufficient to capture these components and support anomaly detection for the targeted operations. [16].

C. Data scope

The dataset spans three production machining centres over a long monitoring period and intentionally reflects real industrial constraints, including machine-to-machine and temporal drift, a variety of operations, and strong class imbalance (degraded states being rare) [16].

III. RESULT AND DISCUSSION

A. Time Domain

Given the very large volume of data, we began with a randomly selected tool; in the scripts, the tool to be analysed can be freely selected. For OP 07 3, the time-domain indicators show a clear increase in the BAD condition, as illustrated in the three tables 1 below:

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Table I: Time-Domain Indicators by Machine – OP 07, X-axis (GOOD vs BAD)

Machine	Status	x_RMS	Δ%_RMS	x_STD	Δ%_STD	x_Kurtosis	x_CrestFactor
M01	Bad	530.236	+28.600	530.235	+28.600	5.468	5.752
	Good	412.168		412.156		9.014	6.260
M02	Bad	501.112	+23.800	500.849	+23.700	5.111	4.241
	Good	404.791		404.785		9.015	5.630
M03	Bad	525.112	+16.000	525.079	+16.100	5.760	5.511
	Good	452.573		452.434		8.424	19.128

Looking at the X-axis (see Table 1), we find a steady rise of RMS from GOOD to BAD state for all three machines. In the case of M01, RMS increases from approximately 412 m to 530 m, a change of about 28% (6%). M02(+23. 8%) and M03(+16. 0%) also display the same kind of behaviour. Standard deviation, too, is on the rise along the same route, and thus, it can be interpreted that during the BAD condition, not only.

The overall vibration level is significantly higher, and it varies more over time. The Y and Z axes behave similarly, with a distinct increase in RMS and standard deviation in the BAD state, notably on the Y-axis of M02, where RMS spikes (Tables 2 and 3). Hence, tool wear is correlated with a substantial increase in vibration levels across all measured axes.

Table II: Time-Domain Indicators by Machine – OP 07, Y-axis (GOOD vs BAD)

Machine	Status	y_RMS	Δ%_RMS	y_STD	Δ%_STD	y_Kurtosis	y_CrestFactor
M01	Bad	317.886	+28.600	316.347	+70.300	8.790	12.665
	Good	188.759		185.754		11.253	14.929
M02	Bad	337.562	+122.100	337.331	+122.000	7.203	7.717
	Good	152.010		151.944		5.722	10.269
M03	Bad	304.165	+40.300	303.899	+40.700	6.557	9.952
	Good	216.738		216.048		10.560	14.995

Table III: Time-Domain Indicators by Machine – OP 07, Z-axis (GOOD vs BAD)

Machine	Status	z_RMS	Δ%_RMS	z_STD	Δ%_STD	z_Kurtosis	z_CrestFactor
M01	Bad	1078.678	+5.100	339.666	+142.900	6.846	3.745
	Good	1026.803		139.824		4.411	1.902
M02	Bad	1092.284	+4.600	321.439	+107.000	4.086	2.852
	Good	1044.568		155.321		4.779	2.403
M03	Bad	1053.560	+0.800	258.990	+17.200	5.052	2.025
	Good	1044.989		221.060		7.104	3.575

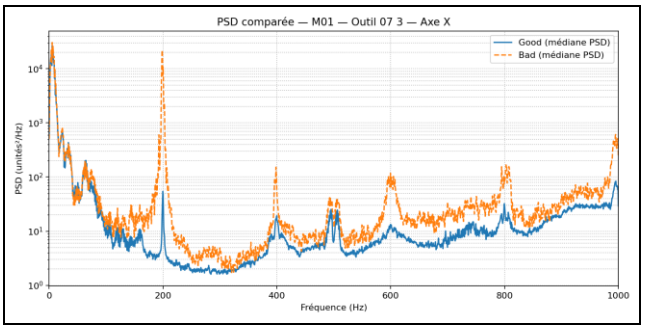
On the other hand, kurtosis and crest factor do not behave in such a straightforward manner. On the X-axis, kurtosis for the GOOD state (usually 8 to 9) is greater than for the BAD state (5, 6), and the crest factor is turned down as the tool deteriorates, especially for the M03. Also, the Y and Z axes show similar tendencies. This suggests that, for this dataset, wear does not primarily manifest as a few strong, isolated shocks; rather, it is reflected in a more continuous increase in vibration energy. In this setting, RMS and standard deviation are more robust time-domain indicators than kurtosis or crest factor for separating GOOD from BAD. It is also important to note that the absolute vibration levels along the X/Y/Z axes are not on the same scale. Expressing changes as a percentage (Δ%) enables fair comparisons across both axes and machines and immediately highlights which direction has truly drifted (e.g., 100% vs 10%) [17]. Formula used:

$$\Delta\% = 100 \times \frac{Bad - Good}{\max(|Good|, \varepsilon)} \quad \ldots \quad (1)$$

ε prevents blow-ups when Good ≈ 0.

B. Frequency domain

On the spectral side, we expect the BAD condition to sit above GOOD over a broad part of the 0–1000 Hz range, especially on the Y-axis, where the RMS/STD increase is the strongest. On X, the gap is more regular but clearly more moderate. On Z, the average level changes only slightly, whereas some frequency bands expand, consistent with the higher STD. Lines around 200/400/600/800 Hz tend to stand out more in BAD, with dB differences that depend on the machine and the axis. We therefore present several global PSD comparisons to provide a broad overview, followed by three targeted zooms in which the markers (band power/peak) are most pronounced.



[Fig.2: M01 · X-axis — PSD Comparison (GOOD vs BAD)]

Figure 2 illustrates, as an example, the comparison of median PSDs for machine M01 on the X-axis (OP 07). The BAD condition shows a globally higher spectral level than GOOD, with clearer separations around a few distinct frequencies. This rise in spectral energy is consistent with the RMS increase observed in the time domain.

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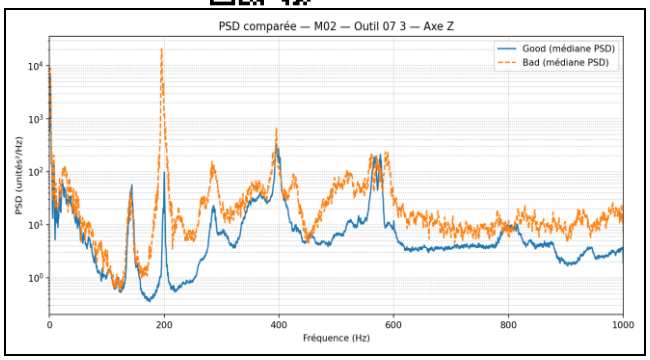
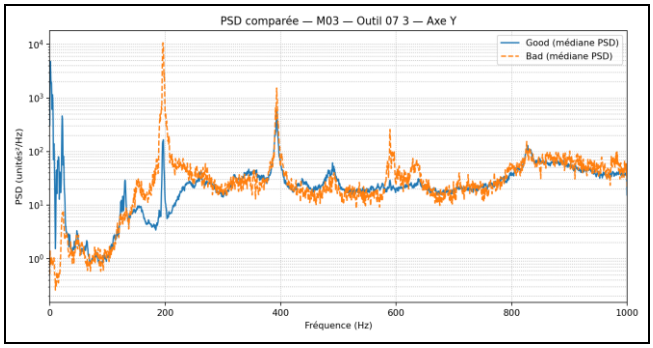


[Fig.3: M02 · Z-axis - PSD Comparison (GOOD vs BAD)]



[Fig.4: M03 · Y-axis - PSD Comparison (GOOD vs BAD)]

Similar behaviours (Figures 3 and 4) are observed on M02 and M03, as well as on the Y and Z axes, even though the magnitude of the differences varies with the machine and the measurement direction.

Table 4 summarizes these values for each machine and each axis. Based on the identified peaks, we then compute, using Eq. (2), for each frequency of interest, a decibel ratio [18] defined as:

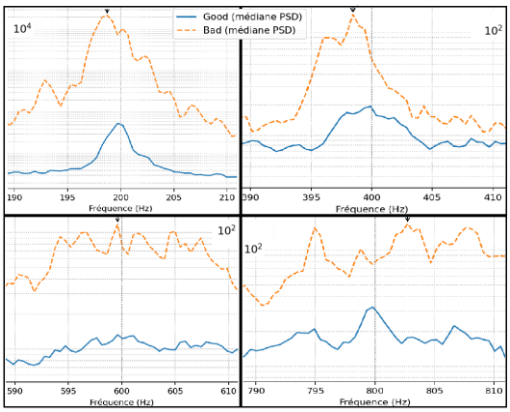
$$\text{ratio_peak_dB}(f_0) = 10\log_{10}\left(\frac{\text{PSD}_{\text{Bad}}(f_{pk})}{\text{PSD}_{\text{Good}}(f_{pk})}\right) \quad \ldots \quad (2)$$

This relation directly expresses, in dB, the spectral-level gap between the worn tool (BAD) and the healthy tool (GOOD) at the frequency of interest.

Table IV: Time-Domain Indicators by Machine – OP 07, X-Axis (GOOD vs BAD)

Tool	Machine	Axis	F_0(Hz)	f_{PK}(Hz)	PSD_Peak_{Good}	PSD_Peak_{Bad}	$ratio_peak_dB$
07	M01	X	200	198.730	25.5562	22041.5	29.3574
07	M01	X	400	398.438	16.2226	151.867	9.71342
07	M01	X	600	599.609	13.3126	117.760	9.46737
07	M01	X	800	802.734	17.6647	167.885	9.77904

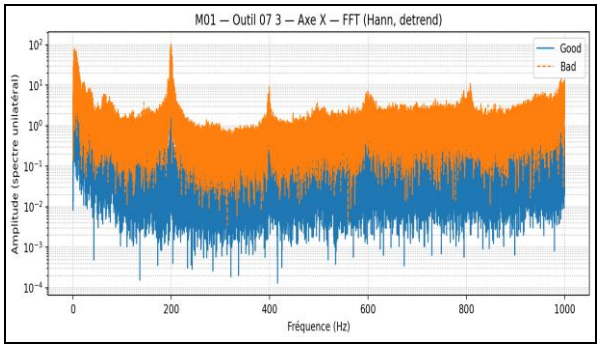
To quantify the differences between GOOD and BAD more precisely, we zoom into narrow bands centred around 200, 400, 600, and 800 Hz. For M01 on the X-axis, Figure 5 shows that the spectral peaks in these bands are clearly higher in BAD, with the strongest contrast around ~200 Hz (about +29 dB), while the other bands show consistent increases around ~9–10 dB.



[Fig.5: Zooms Around 200, 400, 600, and 800 Hz for M01, X-axis, OP 07]

C. Fourier Transform Spectra (FFT)

In addition to the PSD, we use the one-sided FFT amplitude spectrum to examine harmonic components in more detail. For each axis and each machine, the FFT is computed on a representative signal segment using a Hann window, along with a coherent gain correction to preserve amplitude consistency. Figure 6 shows, for M01 on the X-axis, the vibration amplitude spectra in the GOOD and BAD states.



[Fig.6: One-sided FFT Amplitude Spectra for OP 07, Machine M01, X-axis (GOOD vs BAD)]

The lines near 200, 400, 600, and 800 Hz are clearly more pronounced in the BAD state, consistent with the PSD results. FFT markers extracted around these frequencies (amplitude at the closest frequency bin and BAD/GOOD ratio in dB) are reported in Table 7. Around 200, 600, and 800 Hz, the line amplitude increases by a factor of roughly 8 to 30 when the tool is worn, whereas the 400 Hz component shows only a limited increase. These components, therefore, appear to be highly sensitive to tool wear.

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D. Analyse Temps-Fréquence par Transformée en Ondelettes Continues

In this section, we demonstrate how the Continuous wavelet transform (CWT) complements standard time- and frequency-domain analyses and enhances tool-wear diagnosis.

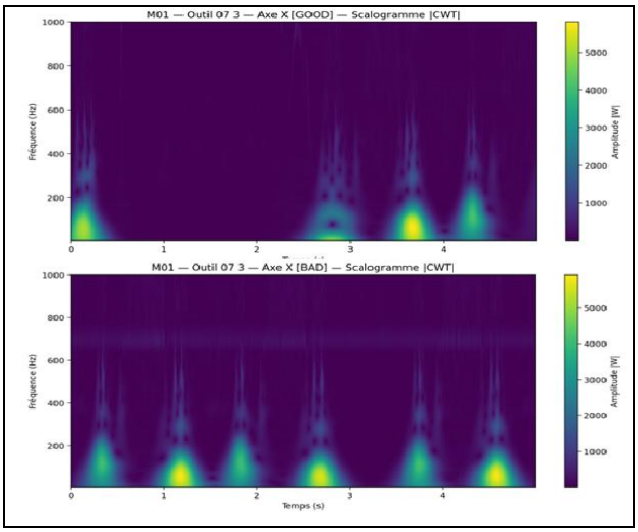
Table V: CWT Markers for M01, OP 07, X-Axis

Tool	Machine	Axis	f0_hz	amp_good	amp_bad	ratio_amp_db	Tool
07	M01	X	200	33.0033	211.016	16.1152	07
07	M01	X	400	24.9619	32.3281	2.24603	07
07	M01	X	600	21.8051	35.7511	4.29463	07
07	M01	X	800	27.9136	41.8524	3.5181	07

Table 5 quantifies the differences in the frequencies of interest 200, 400, 600, and 800 Hz. Around 200 Hz, the mean CWT amplitude increases from roughly 33 in the GOOD state to more than 211 in BAD, corresponding to a gain of about 16 db. The bands around 400, 600, and 800 Hz also increase, but to a lesser extent (typically +2 to +4 dB). These results confirm that the BAD condition concentrates more energy in the same spectral regions highlighted by the PSD and FFT, while also showing that this increase is present on average over the full signal duration.

The average CWT spectrum of M01, OP 07, X-axis indicates that, throughout the 51000 Hz frequency range, the BAD line is always higher than the GOOD line, with the greatest difference at about 200 Hz. This difference in decibels approaches 16 dB at 200 Hz and remains positive at approximately 400, 600, and 800 Hz. The time frequency scalograms also show the same pattern: these frequency bands are excited with greater intensity, wider spread, and longer duration in the BAD state. We observe not only a few isolated peaks but also recurring energy features associated with the machining process. This behaviour is shown in Figure 7.

These observations are consistent with the PSD and FFT analyses: the same frequencies are identified as important; however, the CWT also reveals that their amplitudes remain high throughout the entire time window considered. This verifies that tool wear results in an abnormal vibration pattern which is consistent over time.



[Fig.7: GOOD and BAD Scalograms for M01, OP 07, X-axis]

E. Discussion

We have a multi-level/multi-stage approach to analyse tool wear, which combines time, frequency, and time-frequency analyses. The first observation in the time domain is a significant increase in the overall vibration level (RMS and standard deviation) when the tool is BAD. RMS is a simple and common indicator in vibration monitoring: it is the total energy of the signal. It helps quickly distinguish between the worn (higher RMS) and healthy conditions. However, statistical features such as kurtosis or crest factor are less reliable in this case. According to our experiments, their transition from GOOD to BAD is irregular and therefore unstable when used alone. As highlighted in other papers, the crest factor can increase when defects are present and can provide an early warning if monitored over time; however, it is highly sensitive to random operating conditions and cannot robustly characterise wear. In short, time-domain analysis can be a useful tool for initially separating the GOOD from the BAD state. Still, it is insensitive to changes in the early stages of wear and provides little information about the nature of degradation.

Moreover, frequency-domain analysis highlights an important point: wear cannot be associated with an overall increase in vibration; a significant amplification of certain spectral components also characterises it. Our median PSDs depict the states quite differently, with peaks at 200 Hz, 600 Hz, and 800 Hz that are many times higher in BAD than in GOOD. FFT analysis reveals the same result: the spectral lines corresponding to these frequencies get louder by several tens of decibels when the tool is worn. This is true for all three measurement axes (see the Appendices) and, therefore, wear acts as a source of localised, frequency-specific, periodic excitation, most notably around the 200 Hz frequency. To put it another way, spectral analysis reveals quite reliable frequency markers of wear. Nevertheless, from this standpoint, the perspective is fundamentally time-averaged: it indicates which frequencies are amplified, but not when and how these phenomena manifest during the machining operation (start-up, steady-state, transient variations).

This is why time-frequency wavelet analysis (CWT) is a great help. Initially, it confirms the spectral results by demonstrating that the frequency bands around 200, 400, 600, and 800 Hz are always more energetic in the BAD state. The average CWT spectrum indicates that the average coefficient magnitude (|W|) is higher for the worn tool, with a pronounced peak at approximately 200 Hz, consistent with the dB gap observed in the power spectrum. Most importantly, the scalograms (time frequency maps) bring a new dimension to the analysis: they show the frequency components coming back over time as very high energy patches, sometimes both intermittent and persistent. In simple terms, wear means not only increased total energy but also increased energy at certain times and frequencies;

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certain frequencies are repeatedly used during machining. This detailed characterisation, which can only be achieved through time-frequency descriptors, deepens the physical understanding of the degradation.

IV. CONCLUSION

In conclusion, combining the three analysis stages provides a strong advantage for tool-wear diagnosis. Firstly, time-domain monitoring (RMS, kurtosis, crest factor) enables rapid identification of a global increase in vibration level. Secondly, frequency, domain analysis can reveal individual harmonic signatures, particularly around 200 Hz, that serve as reliable wear markers. And last, but not least, wavelet-based time-frequency analysis supports these findings and demonstrates that these excitations are not just random events. Still, they are persistent and recurrent over time. In fact, the three views combined have considerable detection power, providing both global and local indicators. The novelty of the proposed method lies in its comprehensive viewpoint, which not only increases the confidence in tool wear detection but also clarifies how it manifests in the vibration response. In general, the complementarity of the approaches offers great potential to produce new and more efficient tools for predictive maintenance of cutting operations.

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