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Sensor applications

Health Indicator Analysis in Terms of Condition Monitoring on Brownfield CNC Milling Machines Using Triaxial Accelerometer

Parisa Esmaili* and Loredana Cristaldi**

Department of Electronics, Information and Bioengineering Politecnico di Milano, 20133 Milan, Italy
**Member, IEEE*
***Senior Member, IEEE*

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Abstract—Evaluating the quality of the machining process annotated by experts on the floor in case of developing a silent anomaly is a challenging task. Components wear, wrongly labeled processes, or highly imbalanced data are some examples of real-world difficulties that may prevent the reliability of machine learning algorithms in the manufacturing environment. Since human experts may face several challenges while annotating such high-frequency data, this letter evaluates effective health indexes using time–frequency analysis to extract reliable patterns or vibration signatures assigned to the process quality or bearing health status. A benchmark dataset for process monitoring of Brownfield milling machines over two years is utilized in this letter where the resulting process is evaluated by experts in a gauging station. Vibration signals are collected from three different computer numerical control (CNC) using a triaxial accelerometer, which is mounted on the rear side of the machines. Considering a single operation, the extracted vibration signature is validated on two test CNC machines. As results show, the overall energy level in the frequency range of 0–1 kHz while considering only radial axes gives effective insight into the quality of the process and degradation pattern.

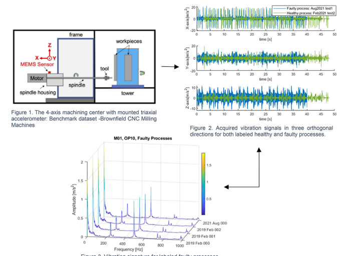

Figure 1. The 4-axis machining center with mounted triaxial accelerometer: Benchmark dataset -Brownfield CNC Milling Machines
Figure 2. Acquired vibration signals in three orthogonal directions for both labeled healthy and faulty processes.
Figure 3. Vibration signature for labeled faulty processes.

Index Terms—Sensor applications, computer numerical control (CNC), condition-based monitoring, discrete Fourier transform, industrial dataset, industry 4.0, quality control, time–frequency analysis, vibration analysis.

I. INTRODUCTION

Additive and subtractive processes are two pillars in modern manufacturing and factories with their applications, benefits, and drawbacks [1], [2]. However, due to market demand and technical progress, such processes are constantly changing with research advancement, which results in modifications in the production speed and process operations. This raises the attention to developing a reliable system for health monitoring [3], [4], [5] and process quality [6], [7] especially in computer numerical control (CNC) machines as one of the most robust and long-standing pillars of the production chain. Prevention of catastrophic failures, predicting tool life, and consequently increasing productivity along with quality are some advantages of comprehensive tool condition monitoring (TCM) systems. However, this requires a system that can correlate the turning variables and tool wear, capable of sensing the changes while addressing their effects on the quality. In [8], an indirect TCM system is discussed in detail. The analysis is devoted to the progression of wear [9] without stopping the operation through sensorial data correlation with tool wear and decision-making methods, such as artificial neural networks, fuzzy logic, and hidden Markov model. Regarding the level of complexity in CNC machining centers in addition to extreme machining environments, tool wear monitoring and analysis become multidomain with high-complexity tasks. Although artificial intelligence techniques can be used as methodology, generalization is still one of the primary challenges for such advanced techniques mainly due to environmental and manufacturing challenges, such as changes in the machining parameters or maintenance methods. To address these real-world conditions and not rely only on laboratory limited-time experiments [10], a challenging CNC research dataset as a benchmark from a real production environment has been published in [11], which is collected over a long period, including different machines and operations. As noted by authors, it contains main challenges that hinder the reliability of ML algorithms in the manufacturing environment, such as missing precise annotations for process quality, wrongly labeled process, high imbalance of healthy and faulty process classes in addition to drift in classes between different time frames because of components wear or hydraulic issues. Therefore, supervising the level of quality for the produced pieces evaluated by experts on the floor while a silent anomaly is developing becomes a worst-case scenario in such a comprehensive database. Addressing such a challenging task requires advanced monitoring of critical components of the machine, which developing wear will cost a significant shot-down. In this letter, the response of the installed triaxial accelerometer on the rear bearing of two different four-axis horizontal CNC machining centers is studied. The approach is to apply short-time Fourier transform (STFT) to extract the vibration signature in addition to evaluate effective health indicators on labeled healthy and faulty processes in such a challenging dataset.

The rest of this letter is organized as follows. Section II presents the methodology for evaluating overall energy distribution in addition to extracting vibration signature, which is discussed in more detail. In Section III, a brief description of the dataset on CNC machine monitoring in addition to the acquired data and its experimental setup is

Corresponding author: Parisa Esmaili. (e-mail: parisa.esmaili@polimi.it).
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presented. Finally, results and conclusions are presented in Sections IV and V, respectively.

II. METHODOLOGY

Evaluating the level of machining quality or process itself only relying on experts on the shop floor may not give information about silent anomaly or tool wear in its early developing stage. Therefore, extracting a vibration signature for each process considering the finishing quality assigned by experts on the shop floor is the main goal. To do this, once the vibration signal is acquired, the challenging task is to analyze it correctly to monitor the vibration levels and patterns within to detect abnormal vibration events in addition to the health status of processes. This can be achieved by studying various parameters, such as root mean square (rms), standard deviation, peak amplitude, kurtosis, crest factor, skewness, and many others [12]. However, special care should be considered while selecting the most effective parameters. To understand vibrations' destructive capability, rms is the most suitable parameter since it is directly related to the energy level. According to the well-known Parseval theorem, which refers to the unitary of Fourier transform, the rms value of a time signal can also be obtained in the frequency domain. Spectrum analysis provides a clear picture of the vibrations because the vibration's frequency together with different frequency components and noise elements can be determined. Such approaches provide additional advantages especially when considering signal processing schemes in real-time monitoring systems where calculations are mostly based on frequency analysis. Therefore, the most intuitive approach is taking the acceleration time domain signal and performing fast Fourier transform. However, due to the nonstationary characteristic of such signals, applying STFT is necessary [13]. Therefore, first, the time signal is segmented into narrow time intervals, and then, it is followed by taking the Fourier transform of each segment. Finally, the rms value is calculated in the band of interest from the obtained spectra. The rms of a spectrum, which is often called the overall level, is a representation of the overall energy in a spectrum and it is evaluated in a range of 10–1000 Hz in most vibration-based condition monitoring.

III. BENCHMARK DATASET FOR CNC MACHINE MONITORING

Although recent developments towards cyber-physical systems and the Internet of Things, opened the doors to digitalization [14], [15], accessing datasets from a real production environment, which are acquired over a long period, plays a crucial role in building robust data-driven models and improving their reliability in the industry.

A. Data Collection

The utilized public dataset in this letter focuses on the quality process failures in addition to some condition anomalies that are detected only after machine maintenance. Three different CNC machines (M0l, M02, and M03) in the production plant are used as test cases. The data are collected regularly during the time interval of October 2018 to August 2021. Each operation represents a specific process performed by a different tool with unique parameters. It is important to mention that the process flow changes over time and the machines produce different parts.

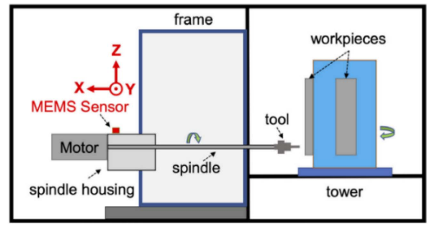

Fig. 1. Schematic sketch of the experimental setup: four-axis machining center with mounted triaxial accelerometer [11].

TABLE 1. Type of Operation and Associated Settings [11]

Tool operation name	Type of action	Speed (r/min)	Feed rate (mm/min)	Operation duration (s)
OP00	End mills	15 000	~6000	~132
OP0l	End mills	15 000	~6000	~29
OP02	Drill	12 000	~3000	~42
OP0S	End mills	1200	~3000	~18
OP06	End mills	15 000	~3000	~91
OP07	End mills	12 000	~3000	~24
OP08	End mills	15 000	~3000	~37
OP10	End mills	15 000	~3000	~45
OP13	T-Slot Cutter	45 000	~1500	~32
OP14	End mills	15 000	~6000	~34

B. Experimental Setup

Data are collected from different four-axis horizontal CNC machining centers during production using a triaxial accelerometer mounted to the rear end of the spindle housing to minimize effects due to the extreme machining environment. Fig. 1 shows the schematic of the experimental setup where three axes of the accelerometer are in alignment with the linear motion axis of the machine. The sampling frequency is 2 kHz and there is no further information from the controller. In this dataset, the machine performs a sequence of several operations following customized design using different tools on aluminum parts. The dataset is built with 15 different tool operations named OP01–OP15 due to the sequence of several operations with specific characteristics of the different speeds, feed rates, durations, and operation types such as end mills, straight, and drill. Table 1 represents a list of some operations with main settings.

For the sack of simplicity, end mills, OP10 with a speed of 250 Hz, feed rate of 50 mm/s, and duration of about 45 s is considered in this letter.

IV. RESULTS AND DISCUSSION

Selecting randomly the period of the test, the acquired time signals on three orthogonal directions by considering both labeled healthy and faulty processes are represented in Fig. 2 for M01. As shown in this figure, the total duration of the process may become longer or shorter. Due to axial forces during machining, the detection between the healthy and faulty processes considering the axial axis (x) is challenging. As shown in this figure, the vibration level is increased in both the y-axis and more evidently in the z-axis for the faulty process.

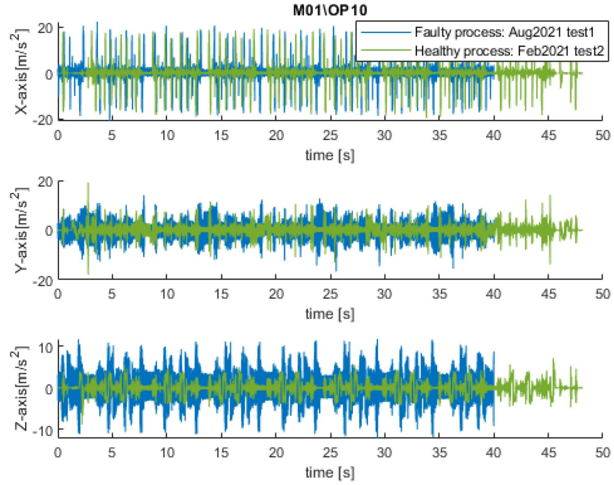

Fig. 2. Comparison between acquired vibration signals on M01 regarding X-Y-Z axes during test 1 in August 2021 and test 2 in February 2021, labeled as faulty and healthy processes, respectively.

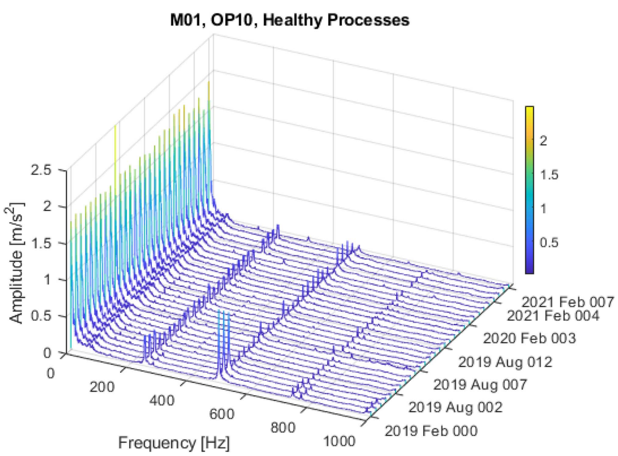

Fig. 3. Vibration Spectrum signature of M01 under OP10 for processes, labeled as healthy processes evaluated from February 2019 to February 2021, including 29 tests considering incremental index.

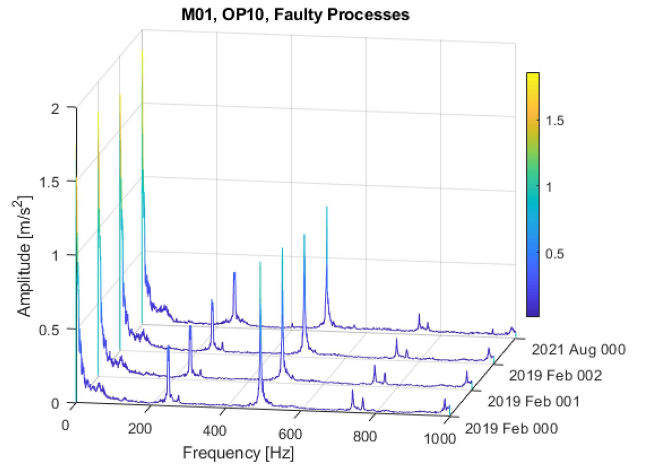

Fig. 4. Vibration Spectrum signature of M01 under OP10 for processes, labeled as faulty processes evaluated between February 2019 and August 2021, including 4 tests with incremental index.

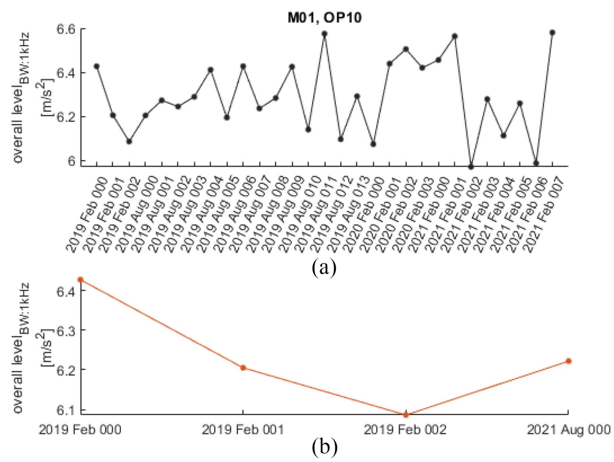

Fig. 5. Absolute value of rms evaluated in the range of 0–1 kHz M01 under OP10 for processes. (a) Labeled as healthy process including 29 tests from February 2019 to February 2021. (b) Labeled as faulty processes evaluated between February 2019 and August 2021, including four tests with incremental index.

It should be mentioned that labeling healthy processes by ignoring the level of vibration is also noted. To extract reliable signatures following the steps mentioned in the methodology sections, M01 is selected as the test machine. The modulus of three orthogonal directions is considered as the output signal, and it is segmented where each window's length is equal to 2.048 s considering 4096 samples. By analyzing the discrete Fourier transform, Fig. 3 shows the spectrogram for the labeled healthy process from February 2019 to February 2021, including 29 tests. The faulty processes are presented in Fig. 4, which were evaluated between February 2019 and August 2021, including only four tests. As mentioned earlier, M01 is performing OP10 at 250 Hz, and comparing the results from STFT, there is a clear growing peak around 500 Hz in addition to low-frequency components and small growth around 750 Hz. Such a pattern can represent bearing degradation or mechanical misalignment. Interestingly, semihealthy processes were observed in the first three labeled healthy processes, which were performed in February 2019. These three processes are called here as semihealthy processes because the vibration signatures are quite similar to assigned faulty processes, as shown in Fig. 4. This can be due to wrong labeling or an indicator of developing a faulty process while the quality is still acceptable. The M02 is considered a second test machine to evaluate the performance of the algorithm to extract the vibration signature on a different test machine whose component's status may be different and the scheduled maintenance is managed differently in terms of time. Similar results on vibration signature were found concerning M02. Following the extracted vibration signature, the overall level in the range of 0–1 kHz is evaluated as the first health indicator or index. Fig. 5 shows the rms for M01 under OP10 for the healthy processes evaluated between February 2019 and February 2021, including 29 tests, and faulty processes evaluated on four tests between February 2019 and August 2021. To compare with the extracted results from the spectrogram, evaluating rms in the interested frequency band seems less sensitive mainly due to dominant lower frequency harmonics.

To improve effectiveness, different approaches, such as changing the frequency band of interest or combining different frequency bands, can be applied in addition to selecting specific axes as customized output. To increase sensitivity by removing axial forces during machining and consequently excluding the x-axis, the resulting overall level for the same frequency band is represented in Fig. 6. As shown in this figure,

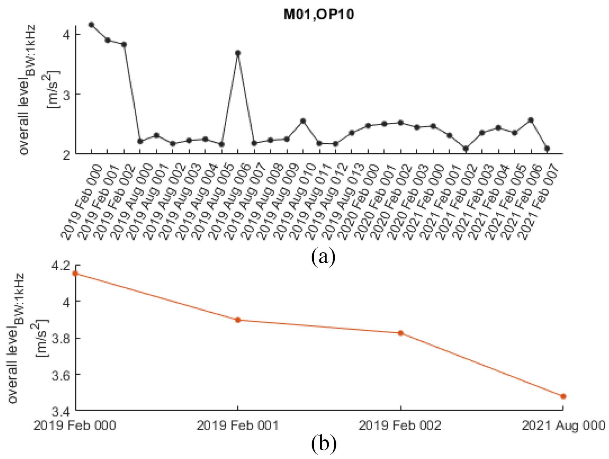

Fig. 6. RMS value excluding the *x*-axis, evaluated in the range of 0–1 kHz M01 under OP10 for processes. (a) Labeled as healthy process from February 2019 to February 2021. (b) Labeled as faulty processes evaluated between February 2019 and August 2021, including four tests.

it is evident that the defined health index reports an increased level of energy following extracted results from the spectrogram. Also in this figure, for the first three processes that were performed in February 2019, the health indicator represents much higher values than the rest. This highlights an abnormal behavior regarding the bearing's status while the result of the process on the gauging station is assigned as acceptable quality.

V. CONCLUSION

Concerning a tradeoff between a reliable TCM system and final product quality while addressing industrial challenges, this letter evaluates the impact of the critical component's vibration signature regarding the process quality. To do this, a challenging public dataset of Brownfield milling machines containing vibration signals for CNC machines is utilized as a benchmark. The dataset is built on 15 different tool operations and contains "good" and "bad" labels as the quality of the final product evaluated by the gauging station. The triaxial accelerometer is installed on the rear bearing and the signal is acquired at 2 kHz. In this letter, Eed mills (OP10) with a speed of 250 Hz, feed rate of 50 mm/s, and duration of about 45 s is considered. To extract the vibration signature, the modulus of three orthogonal directions is considered as the output signal, and it is segmented where each window's length is equal to 2.048 s. As a first step and in an unsupervised approach, there is a clear difference in the spectrogram of healthy and faulty processes. Comparing this result with assigned labels, an interesting confusion is observed that may be a result of wrong labeling or growth of salient anomaly. A further step is considered by evaluating the overall energy in a spectrum in a range of 0–1 kHz as a simple health indicator. As results show, the defined health index demonstrates a reliable performance to reflect the quality of the process and degradation pattern. However, to reach comprehensive monitoring and prediction, further indexes are required to be extracted, which is the future step of this work considering different operations and machines.

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REFERENCES

[1] X. F. Li et al., "A review of recent advances in machining techniques of complex surfaces," *Sci. China Technol. Sci.*, vol. 65, no. 9, pp. 1915–1939, 2022, doi: 10.1007/s11431-022-2115-x.

[2] P. Qiao, Q. Tang, T. Hu, and H. Zhang, "Post-processing technology of the five-axis additive–subtractive composite manufacturing machine tool," *Int. J. Adv. Manuf. Technol.*, vol. 131, no. 1, pp. 409–424, 2024, doi: 10.1007/s00170-024-13095-9.

[3] D. F. Hesser and B. Markert, "Tool wear monitoring of a retrofitted CNC milling machine using artificial neural networks," *Manuf. Lett.*, vol. 19, pp. 1–4, 2019, doi: 10.1016/j.mfglet.2018.11.001.

[4] T. Mohanraj, S. Shankar, R. Rajasekar, N. R. Sakthivel, and A. Pramanik, "Tool condition monitoring techniques in milling process-A review," *J. Mater. Res. Technol.*, vol. 9, no. 1, pp. 1032–1042, 2020, doi: 10.1016/j.jmrt.2019.10.031.

[5] D. Y. Pimenov, L. R. R. da Silva, A. Ercetin, O. Der, T. Mikolajczyk, and K. Giasin, "State-of-the-Art review of applications of image processing techniques for tool condition monitoring on conventional machining processes," *Int. J. Adv. Manuf. Technol.*, vol. 130, no. 1–2, pp. 57–85, 2024, doi: 10.1007/s00170-023-12679-1.

[6] Z. Lu, M. Wang, and W. Dai, "Machined surface quality monitoring using a wireless sensory tool holder in the machining process," *Sensors*, vol. 19, no. 8, 2019, Art. no. 1847, doi: 10.3390/s19081847.

[7] V. Nguyen and S. N. Melkote, "Manufacturing process monitoring and control in industry 4.0," in *Proc. 5th Int. Conf. Industry 4.0 Model Adv. Manuf.*, 2020, pp. 144–155.

[8] M. K. Gupta, T. Mikolajczyk, K. Giasin, and W. Kapłonek, "A review of indirect tool condition monitoring systems and," *Sensors*, vol. 21, 2021, Art. no. 108, doi: 10.3390/s21010108.

[9] A. Muhammad, M. K. Gupta, T. Mikołajczyk, D. Y. Pimenov, and K. Giasin, "Effect of tool coating and cutting parameters on surface roughness and burr formation during micromilling of Inconel 718," *Met. (Basel)*, vol. 11, no. 1, 2021, Art. no. 167, doi: 10.3390/met11010167.

[10] I. Kovalenko, M. Saez, K. Barton, and D. Tilbury, "SMART: A system-level manufacturing and automation research testbed," *Smart Sustain. Manuf. Syst.*, vol. 1, 2017, Art. no. 20170006, doi: 10.1520/SSMS20170006.

[11] M. A. Tnani, M. Feil, and K. Diepold, "Smart data collection system for brownfield CNC milling machines: A new benchmark dataset for data-driven machine monitoring," *Procedia CIRP*, vol. 107, pp. 131–136, 2022, doi: 10.1016/j.procir.2022.04.022.

[12] E. Iunusova, M. K. Gonzalez, K. Szipka, and A. Archenti, "Early fault diagnosis in rolling element bearings: Comparative analysis of a knowledge-based and a data-driven approach," *J. Intell. Manuf.*, vol. 35, pp. 2327–2347, 2024, doi: 10.1007/s10845-023-02151-y.

[13] V. Dekys, P. Kalman, P. Hanak, P. Novak, and Z. Stankovicova, "Determination of vibration sources by using STFT," *Procedia Eng.*, vol. 177, pp. 496–501, 2017, doi: 10.1016/j.proeng.2017.02.251.

[14] A. Quatrano, M. C. De Simone, Z. B. Rivera, and D. Guida, "Development and implementation of a control system for a retrofitted CNC machine by using Arduino," *FME Trans.*, vol. 45, no. 4, pp. 565–571, 2017, doi: 10.5937/fmet1704565Q.

[15] R. G. Lins, B. Guerreiro, R. Schmitt, J. Sun, M. Corazzim, and F. R. Silva, "A novel methodology for retrofitting CNC machines based on the context of Industry 4.0," in *Proc. IEEE Int. Symp. Syst. Eng.*, 2017, pp. 1–6, doi: 10.1109/SysEng.2017.8088293.

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