Unlocking Tool Wear Information from Spindle Current Signals: An explorative Energy-Based Analysis using the NASA Milling Dataset

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Abstract—**Reliability of milling processes is affected by accurate tool wear estimation due to its direct impact on product quality, energy consumption, process stability and, indirectly related to productivity and costs. In CNC milling, the progressively worn tool increases friction and this results in major mechanical resistance with a consequence of higher energy requirements on fixed cutting conditions. In this context, the continuous monitoring of energy-related signals, captured by sensors installed directed on CNC spindle, represents a non-invasive solution to derive Physical-informed Machine Learning (PiML) approach for a predictive production. It can derive wearing condition by alternative managing operational condition and production (as per material and task) schedule. This paper, starting from the NASA Prognostics Center of Excellence (PCoE) Milling Wear dataset, investigates the relationship between spindle electrical current signals, considering both the direct current (DC) and alternating current (AC) components, and tool flank wear (VB) in cast iron and steel bar milling operations. The separation of the DC and AC components enables modulation of the electrical signal in order to distinguish the contribution of the average energy load, associated with cutting conditions, from the dynamic variability of the process, related to tool–workpiece interaction phenomena and load fluctuations. The steady-state cutting phase is captured to avoid influence of transient effects associated to approach/ejection movement to material removal. From the AC and DC signals, by using Principal Component (PC) decomposition, authors generated the global energy behaviour associated with wearing progression. Results highlight a relationship DC-based indicators and flank wear.**

I. Introduction

The growing need for sustainable processes in industrial milling operation is currently driving by the proactive assignment of optimal balance between machine performances, product quality with power efficiency [1]. The understanding of the material removal process is, then, essential for selecting and managing cutting tools, as well as for ensuring dimensional accuracy and adequate surface product's integrity. In subtractive manufacturing, friction influences cutting power, tool life and process availability, product quality and production costs [2]. As wearing in tool increases, cutting forces, vibrations, and temperature rise, leading to deterioration of surface integrity and dimensional errors beyond tolerance limits [3]. The tool needs, then, replacement or recondition, interrupting the machining process [4]. Therefore, predicting friction in metal cutting can improve process efficiency and optimize machining performance [5] and system's productivity [6]. Tool wear is mainly assessed by indirect (i.e., post worked) measurement of the geometric–dimensional characterization and surface integrity of a component manufactured, with reference to dimensional tolerances and surface roughness [7]. According with Kious et al., (2000) [8], tool condition monitoring mainly relies on the observation of wear and damage, achieved through different sensing modalities. The most datasets makes use of acoustic signals [9 10], vibration signals [11], current signals [12] and cutting force signals [13]. Among these, current signals present the advantage of being directly acquired without requiring the installation of additional external sensors, thus reports relevant industrial applicability [14]. Motor current sensors for Tool condition monitoring (TCM) are not intrusive, easy to install and cost effective [15]. By monitoring the evolution of current signals, tool degradation can be derived, since wear conditions lead to variations in the waveform and amplitude of the signal, providing useful information for timely tool replacement and maintenance planning [16]. The specific energy at each level increases significantly as tool degradation progresses [17]. Wear in tool determines rise of the cutting forces, particularly in down-milling, due to the greater contact area [18]. Zhou & Sun (2020) [19] and Karabacak et al., (2024) [20] used the NASA Milling Dataset [21] to develop and trainee Physical-informed Machine Learning (PiML) models. They are suggesting the application of Improved Kernel Extreme Learning Machine (KELM), Short-Time Fourier Transform (STFT), and Convolutional Neural Networks (CNN).

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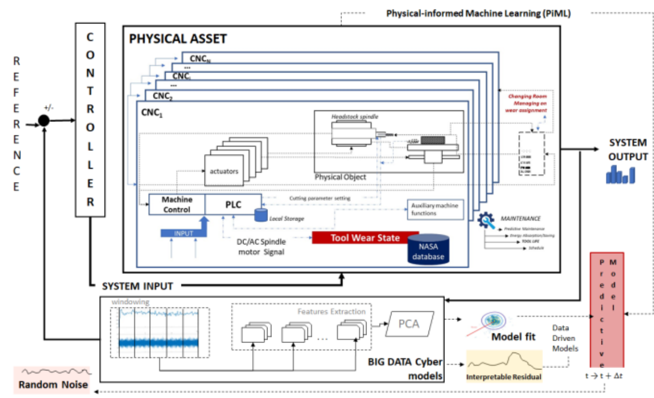

Figure 1. Physical informed Machine Learning (PiML) framework (as per 23) integrating Tool Wear Management on AC/DC spindle motor signals for Optimal Assignment

However, the potential of predictive approaches based exclusively on current signals remains relatively underexplored in the literature [22]. The aim of this work is to derivate the potential of electrical signals, in particular spindle motor current, as a non-invasive indicator for tool wear prediction in milling processes. Since tool wear is affecting the energy demand of the process, using spindle motor can contribute to optimal assign subtractive tasks and schedule production assignment in advanced multi milling systems (figure 1). Specifically, the study focuses on the Tool Wear State module integrated in a PiML for real time prediction. It extracts physically interpretable energy-related features from AC and DC spindle current signals, normalized over the machining cycle, in order to evaluate their correlation with tool flank wear (VB) and their suitability for predictability. The use of both signal components is motivated by their complementary physical meaning: the DC component reflects the average energy demand associated with cutting load, while the AC component captures the dynamic variability of the process related to tooth engagement, vibrations, and load fluctuations [24]. Principal Component Analysis (PCA) is used to statistically identify the most informative features [25]. In light of these considerations, the present study aims to investigate the relationship between energy-related indicators derived from spindle electrical current signals on the progression of tool wear. Furthermore, the study aims to identify a correlation between machine electrical current behaviour and spindle load, in order to support the early prediction of tool replacement, enabling more timely and reliable maintenance decisions. The paper addresses two Research Questions:

RQ1. How does tool flank wear (VB) influence the shape and energy level of spindle electrical current profiles (AC and DC components) during milling operations?

RQ2. Which energy-related features extracted from spindle electrical current signals show the strongest relationship with the progression of tool flank wear?

The remainder of the paper is organized as follows: section II describes the adopted methodology, including the NASA dataset and the procedure for extracting energy-related features derived from spindle current signals. Section III presents the obtained results, analysing the relationship between the extracted features and tool wear, and discussing (section IV) the significance of the results as per predictivity of production performances sonsorized industries. Finally, section V presents the main conclusions of the work and outlines possible future developments in the field of predictive maintenance.

II. METHODOLOGY

The experimental analysis is based on data obtained from the NASA Milling Dataset [21]. The basic setup includes Matsuura MC-510V machining center. The experimental data were collected at the cutting speed of 200 m/min, corresponding to 826 rev/min. Two values of depth were settled over experiments (i.e., 1.5 mm and 0.75 mm) on two feed rates (i.e., 0.5 mm/rev and 0.25 mm/rev, corresponding to 413 mm/min and 206.5 mm/min, respectively). The experiments were conducted with two materials, cast iron and J45 steel, using KC710 inserts. The combination of these parameters resulted in eight different machining conditions. All experiments were repeated twice, using a second set of inserts, for a total of 16 cases. The dimensions of the workpieces were 483 mm × 178 mm × 51 mm. An acoustic emission sensor and a vibration sensor were mounted on both the spindle and the machine table. The signals acquired from the sensors are amplified and filtered, and subsequently processed through two RMS conversion stages before being transmitted to the data acquisition system. In contrast, the signal from the spindle motor current sensor is directly collected. For each run, corresponding to an individual experimental test, the flank wear (VB) of the cutting tool was measured, and all acquired data were organized in a MATLAB struct array (1×167) composed of 13 fields. Each experimental run consists of time-series signals composed of multiple samples describing the electrical behaviour of the spindle throughout the machining cycle. In this study, after featuring data over experiments, Case 1 (corresponding to the milling of cast iron with a depth of cut of 1.5 mm and a feed rate of 0.5 mm/rev) from the dataset was mainly analyzed. Furthermore, we extracted correlations from signals of Cases 1, 2, 3, 7, 11, 12, and 13 of the NASA Milling dataset, considering comparable wear levels ($0 \leq VB \leq 0.37$ mm). Material influence on data was investigated (i.e., Cases 1, 2, 3, 11, and 12 correspond to cast iron machining, whereas Cases 7 and 13 refer to steel machining). The DC and AC current signal trends were extracted and used for an exploratory analysis of signal behavior as the runs progressed and, consequently, as flank wear degradation evolved. Subsequently,, energy-related features were extracted and analyzed from the cases containing the highest number of available runs in the dataset. These features were then used for the PCA-based analysis In order to improve signal readability while preserving the physical characteristics of the process, a normalization of signals was applied to both AC and DC signals, reducing high-frequency noise without altering the overall signal trend. Specifically, each signal was rescaled along the horizontal axis so that the machining cycle spans from 0% to 100% of its duration, ensuring consistency across runs. A plateau region was isolated within the normalized cycle to avoid transient error. In particular, the interval between 20% and 80% of the normalized cycle was selected to approximate the steady-state cutting phase [26]. This isolate tool entry and exit absorption, which typically occur at the beginning and at the end of the machining process. During these phases, the cutting system is affected by rapid variations in chip thickness, impact loads, and forced vibrations generated by the intermittent engagement between tool and workpiece [27]. The extracted plateau region are representative of the cutting load and this gain extraction of energy-related features correlated with VB. From the plateau region of the normalized cycle, energy-related features was selected from AC and DC spindle current signals [28]. DC features describe the average cutting load and energy demand, including mean current level, maximum value, signal variability, energy indicator, and slopes associated with tool engagement and disengagement phases. AC features describe the dynamic behaviour of the cutting process and include indicators related to oscillation amplitude, signal variability, dynamic energy content, and short-term load fluctuations [24]. These features provide physically interpretable descriptors of the cutting process and are expected to be sensitive to tool wear progression [16]. Principal Component Analysis (PCA) was applied from AC and DC spindle current signals in order to identify the dominant patterns of variability associated with tool wear. The first principal components was analyzed in terms of explained variance and correlation with flank wear VB. It was correlated with internal variables affecting directions of variability. In particular, the analysis was carried out by considering the runs belonging to Cases 1, 2, 3, 7, 11, 12, and 13 of the NASA Milling dataset, selecting samples characterized by wear values ranging from VB = 0 to a wear level close to VB≈0.37 mm. This approach made it possible to compare the behavior of the principal components under different operating conditions while maintaining comparable degradation levels. The analysis allows evaluating whether combined energy-related indicators can effectively describe tool degradation trends.

III. RESULTS

A cross-case comparative analysis was conducted across cases and tests at fixed levels of flank wear in order to enable a consistent evaluation of energy-related indicators under different materials and process parameters. The Root Mean Square (RMS) value was calculated over tests characterized by the same cutting parameters, material, and VB value, considering at least six available runs.

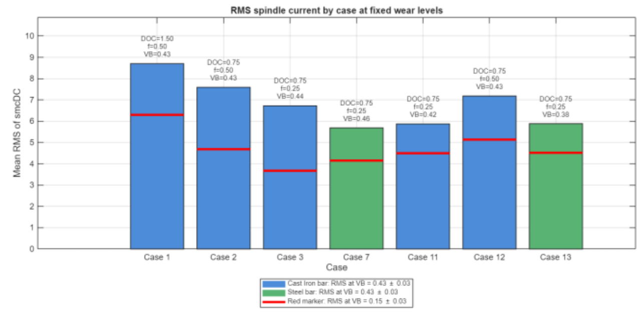

Figure 2. Comparison of mean RMS spindle current across cases 1, 2, 3, 7, 11, 12, 13, at fixed levels of flank wear (VB ≈ 0.15 and VB ≈ 0.43), highlighting the increase in energy demand with tool wear.

In particular, Cases 1 (DOC 1.5, f 0.5), 2 (DOC 0.75, f 0.5), 3 (DOC 0.75, f 0.25), 11 (DOC 0.75, f 0.25), and 12 (DOC 0.75, f 0.5) refer to cast iron machining, whereas Cases 7 (DOC 0.75, f 0.25) and 13 (DOC 0.75, f 0.25) refer to steel machining. As reported in Fig. 2, at a fixed flank wear level of 0.44 mm, the RMS value of the spindle current exhibits higher values compared to lower VB levels (≈0.15 mm). This indicates an increase in the average energy demand as tool degradation progresses, consistently with findings reported in the literature [22, 24]. This effect is much more pronounced in cast iron machining than in steel machining [29]. The comparison suggests that the depth of cut exerts a greater influence on energy consumption in steel machining, whereas feed rate variations are more significant in cast iron machining. In Fig. 3, the raw signals acquired from the AC and DC current sensors of the machine are shown for Case 1 – Run 17 (VB = 0.44 mm). The initial portion of the signal corresponds to the engagement of the cutting tool with the workpiece, characterized by an increase in electrical load due to the transition from near-idle conditions to material removal. The subsequent stage represents the steady-state machining region, in which the tool operates under relatively stable cutting conditions. The third portion corresponds to the disengagement of the tool from the workpiece, during which the electrical load progressively decreases as the cutting forces are reduced and the process returns toward near-idle conditions, while still passing through a zone characterized by residual friction.

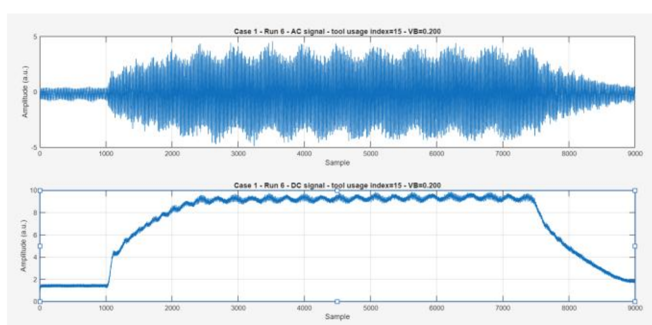

Figure 3. Raw AC and DC signals for Case 1 – Run 6 (VB = 0.20 mm). The DC component shows the average spindle load during steady cutting.

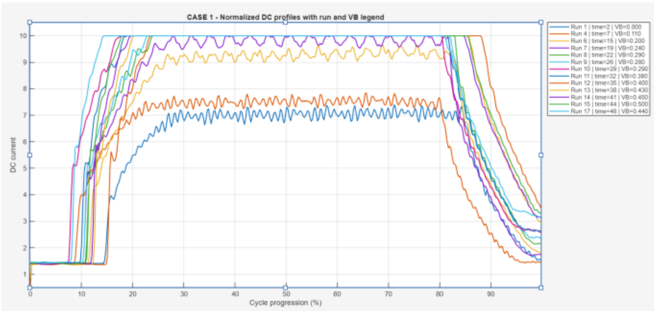

Figure 4. Normalized DC spindle current profiles for Case 1 at different tool wear levels (VB), colored lines, over Runs

The AC and DC signals were normalized for alignment of the energy profiles along a common temporal scale, facilitating the identification of recurring patterns and the extraction of comparable features. In Fig. 4, the normalized DC current profiles exhibit trend across the machining experiments, confirming the repeatability of the machining cycle structure. The steady-state cutting region (approximately between 30% and 70% of the cycle progression) is characterized by relatively stable signal levels that progressively vary as tool wear increases. An increase in the DC current level can be observed for higher VB values, indicating a higher average electrical load required to sustain the cutting process under worn tool conditions. At higher wear levels, normalized DC profiles approach the upper bound of the signal range, causing a partial flattening of the steady-state plateau, which reflects increased cutting forces and leads to a higher and more stable average spindle load. As the DC signal has nearly linear relationship between voltage/speed and current/torque it becomes more regulable and less sensitive to small load variations under highly worn conditions. Conversely, localized effects alter the AC component, which remains more sensitive to the dynamic aspects of the cutting process. Conversely, the normalized AC current profiles do not exhibit a clearly observable monotonic trend as tool wear increases. Compared to the DC component, the AC signal shows higher variability, as it is more sensitive to dynamic phenomena such as the periodic engagement of the cutting edges, process vibrations, and local cutting instabilities. To further investigate the relationship between tool wear and the dynamic component of the spindle current, the standard deviation of the absolute AC current signal was extracted from the steady-state cutting region of the normalized cycle (30–70%), where process conditions are more stable and less affected by transient effects. In Fig. 5, the extracted feature exhibits a moderate negative correlation with tool wear ($r = -0.490$), indicating that the variability of the AC signal tends to slightly decrease as flank wear increases. This suggests the cutting process is negatively related to tool wear conditions, due to the increase of contact area between worn tool flank and workpiece. The AC-based feature still provides information about dynamics.

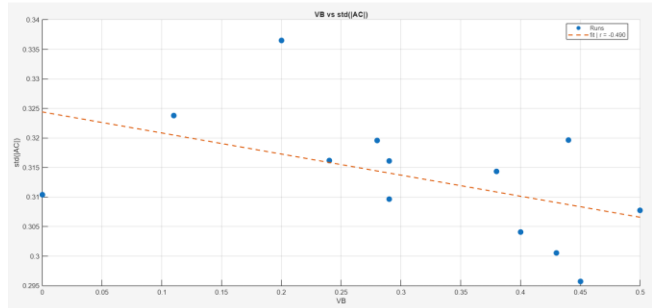

Figure 5. Oscillation amplitude vs tool wear in Case 1. Moderate negative correlation ($r \approx -0.490$) indicates reduced dynamic variability with increasing wear.

Energy-related features derived from both the DC and AC components of the spindle current were evaluated with respect to tool flank wear (VB). Fig. 6 summarizes the relationship between VB and the main statistical descriptors computed within the steady-state cutting region (30–70% of the normalized cycle) between AC and DC signals. The selected indicators describe the dynamic variability of the spindle current signal as per the energy consumption. For the DC component, the extracted features include the mean value of the signal in the steady-state region (DC mean plateau), the maximum value (DC max plateau), the standard deviation (DC std plateau), an energy-related indicator computed as the integral of the signal (DC energy plateau), and the slopes associated with the tool engagement and disengagement phases (DC rise slope and DC fall slope). The mean value of the DC signal exhibits the highest correlation with tool wear ($r \approx 0.85$), followed by the energy-related feature and the slope of the signal during the engagement phase. For the AC component, the standard deviation of the absolute AC signal (std(|AC|)), the mean value of the smoothed absolute signal, the energy of the AC component within the steady-state region, the oscillation amplitude, and the local peak-to-peak variation are computed as main features. with VB ($r \approx -0.70$), indicating that the variability of the dynamic component tends to slightly decrease as tool wear progresses. The AC oscillation amplitude reports the strongest correlation.

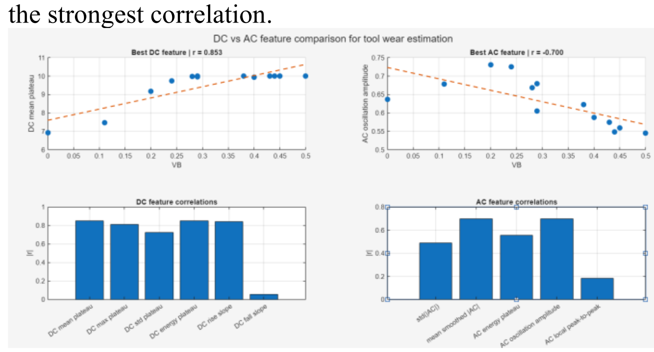

Figure 6. Comparison of DC and AC energy-related features in Case 1 for tool wear estimation. DC indicators show strong positive correlation with VB, while AC features describe the dynamic behaviour of the cutting process.

This behaviour is consistent with the progressive stabilization of the contact conditions between the worn tool flank and the workpiece, which may lead to more regular fluctuations of the cutting forces [24]. To highlight the main sources of variability and identify the dominant patterns associated with tool wear progression, PCA was applied to a selected set of energy-related features extracted from AC and DC spindle current signals, including DC mean plateau, DC energy plateau, AC energy plateau and AC std(abs) The results show that the first principal component (PC1) accounts for approximately 60% of the total variability of the dataset, thus representing the most significant component describing the overall energy-related behavior of the process. The DC mean plateau, DC energy plateau and AC energy plateau features across the analyzed cases, suggested that the dominant source of variability is associated with the increase in energy demand as tool wear progresses. In contrast, the AC std(abs) exhibits the highest sensitivity to local effects dynamics such as vibrations and cutting instabilities. In particular, the steel machining cases reports pronounced differences in the dynamic component compared to the cast iron cases.

IV. DISCUSSION

The obtained results confirm that the energy-related features extracted from spindle current signals contain meaningful information about tool wear progression. In particular, the features derived from the DC component reported the strongest relationship with VB, especially the mean value computed in the steady-state region, which exhibits the highest correlation coefficient. Conversely, Energy-related indicators derived from the AC component capture the dynamic characteristics of the cutting process, such as load oscillations associated with tooth engagement and process vibrations. The observed decrease in oscillation amplitude with increasing wear suggests a slight stabilization of the cutting process dynamics. This effect may be attributed to the enlargement of the contact area between the worn flank surface of the tool and the workpiece, which can produce more regular load fluctuations and reduced variability in the dynamic component of the current signal.

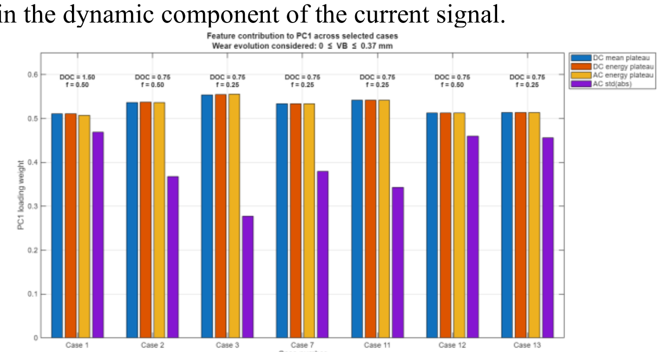

Figure 7. PC1 loading coefficients of the selected energy-related features from AC and DC spindle current from NASA Milling dataset (0≤VB≤0.37mm) - over cases.

Despite the different cutting conditions in terms of depth of cut (DOC) and feed rate (f), the steady-state energy-related features gains a consistent contribution to the principal variability direction associated with tool wear. This replies RQ1. The PCA results further support the relevance of the extracted features, showing that a large portion of the variability of the dataset can be explained by a limited number of principal components. In particular, as per RQ2, Fig. 7 remarks the contribution of each feature to the first principal component (PC1). The dominant role of the first principal component indicates that the main information related to tool wear progression is largely contained in a reduced set of energy-related indicators, mainly associated with the average level of absorbed energy. The identified relationships between energy-related indicators and tool wear provide useful insights for the development of predictive maintenance strategies based on easily accessible process data [30]. In particular, the possibility of describing tool degradation through a limited number of physically interpretable energy-related features supports the implementation of data-driven models capable of estimating tool condition and anticipating maintenance needs (as per the PiML framework of fig.1). This approach enables cost-effective monitoring solutions based on signals already available within the CNC system, reducing the need for additional instrumentation while maintaining reliable diagnostic capability. The identified features can be directly embedded into CNC monitoring systems or supervisory software to enable real-time tracking of tool condition without the need for additional sensors.

V. CONCLUSION

Within the broad landscape of predictive maintenance strategies, the results of this study provide a clear and physically grounded framework for exploiting energy-related signals as reliable indicators of tool condition. The analysis demonstrates that spindle current signals, which are inherently available in CNC systems, can be effectively transformed into a reduced set of physically interpretable features capable of capturing the progression of tool wear. In particular, indicators associated with the average energy demand of the cutting process, primarily derived from the DC component, have been shown to exhibit a strong and consistent relationship with flank wear. At the same time, features extracted from the AC component provide complementary information related to the dynamic behaviour of the process, enabling a more comprehensive characterization of machining conditions. The combined interpretation of these features allows the construction of a coherent and physically meaningful representation of tool degradation. From an application-oriented perspective, the strong correlation between selected energy indicators and tool wear supports the development of data-driven models capable of estimating tool health and predicting the remaining useful life (RUL) of the tool. Moreover, the dimensionality reduction achieved through PCA enables the design of computationally efficient monitoring algorithms suitable for real-time applications and edge computing environments. Overall, the proposed approach provides a scalable and cost-effective pathway for the implementation of predictive maintenance strategies based on energy profiles. By leveraging signals already available within the machine tool, it reduces system complexity while maintaining high diagnostic capability. These results are going to be integrated in a data-driven decision-making processes for reliability and operational improvement in production.

REFERENCES

[1] Z. M. Çınar, A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, "Machine learning in predictive maintenance towards sustainable smart manufacturing in Industry 4.0," Sustainability, vol. 12, no. 19, p. 8211, 2020.

[2] S. Gao, X. Wang, H. Zakaria et al. "Research progress on friction reduction by surface texture control through subtractive manufacturing and related techniques: a review". Surf. Sci. Technol. 4, 6, 2026. https://doi.org/10.1007/s44251-025-00121-5

[3] S. Zhang, Z. Zhang, L. Lu, Z. P.V. Wang, "Overview on material removal mechanisms and surface textures modelling in abrasive jet machining processes". Int J Adv Manuf Technol 137(7):3165–3213 (2025). https://doi.org/10.1007/s00170-025-15300-9

[4] Z. T. Abdullah. "Conventional milling into CNC machine tool remanufacturing: Sustainability modeling." Economics, Management and Sustainability 5.2 (2020): 39-65.

[5] M. Nouri, B. K. Fussell, B. L. Ziniti, E. Linder, "Real-time tool wear monitoring in milling using a cutting condition independent method", Int. J. Mach. Tools Manuf., 89, 1–13, 2015.

[6] K. Tarcisio Filho, R. T. Coelho, A. E. Diniz, and E. O. Ezugwu, "An analysis of different cutting strategies to improve tool life when machining Ti-5Al-5V-5Mo-3Cr alloy," Journal of Manufacturing Processes, vol. 102, pp. 50–66, 2023.

[7] D.E. Dimla Sr., "Sensor signals for tool-wear monitoring in metal cutting operations—A review of methods," International Journal of Machine Tools and Manufacture, vol. 40, no. 8, pp. 1073–1098, 2000.

[8] M. Kious, A. Ouahabi, M. Boudraa, R. Serra, A. Cheknane, "Detection process approach of tool wear in high speed milling", Measurement, 43(10), 1439–1446, 2010.

[9] P. Goodall, D. Pantazis, and A. West, "A cyber physical system for tool condition monitoring using electrical power and a mechanistic model," Computers in Industry, vol. 118, p. 103223, 2020.

[10] M. Farahnakian, M. Eynian, M. Razfar, and M. Amini, "Effect of cutting edge modification on the tool flank wear in ultrasonically assisted turning of hardened steel," Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, vol. 233, no. 5, pp. 1472–1482, 2019.

[11] N. Barari, S. A. Niknam, and H. Mehmanparast, "Tool wear morphology and life under various lubrication modes in turning stainless steel 316L," Transactions of the Canadian Society for Mechanical Engineering, vol. 44, no. 3, pp. 352–361, 2019.

[12] H. Mostaghimi, M. J. Jackson, and M. Park, "Reconstruction of cutting forces through fusion of accelerometer and spindle current signals," Journal of Manufacturing Processes, vol. 68, pp. 990–1003, 2021.

[13] K. N. Shi, D. H. Zhang, N. Liu, S. B. Wang, J. X. Ren, S. L. Wang, A novel energy consumption model for milling process considering tool wear progression, J. Clean. Prod., 184, 152–159, 2018.

[14] K. Zhu and Y. Zhang, "A generic tool wear model and its application to force modeling and wear monitoring in high speed milling," Mechanical Systems and Signal Processing, vol. 115, pp. 147–161, 2019.

[15] S. Bombiński, J. Kossakowska-Skajster, & K. Jemielniak, "New developments and future prospects in commercial tool condition monitoring systems". Measurement, 255, 118037 (2025).

[16] Z. Y. Liu, Y. B. Guo, M. P. Sealy, Z. Q. Liu, "Energy consumption and process sustainability of hard milling with tool wear progression, J. Mater. Process. Technol., 229, 305–312, 2016.

[17] Y. Su, C. Li, G. Zhao, C. Li, and G. Zhao, "Prediction models for specific energy consumption of machine tools and surface roughness based on cutting parameters and tool wear". Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 235(6-7), 1225-1234, 2021.

[18] A. Gavahian and C. K. Mechefske, "Motor current-based degradation modeling for tool wear hybrid prognostics in turning process," Machines, vol. 11, no. 8, p. 781, 2023.

[19] Y. Zhou and W. Sun, "Tool wear condition monitoring in milling process based on current sensors," IEEE Access, vol. 8, pp. 95491–95502, 2020.

[20] Y. E. Karabacak, "Intelligent milling tool wear estimation based on machine learning algorithms," Journal of Mechanical Science and Technology, vol. 38, no. 2, pp. 835–850, 2024.

[21] NASA Prognostics Center of Excellence, "Milling Machine Data Set," NASA Ames Research Center, Moffett Field, CA, USA. [Online]. Available: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/

[22] A. Dietmair, A. Verl, "Energy consumption forecasting and optimisation for tool machines". CIRP Annals – Manufacturing Technology 58(1), 63–66, 2009.

[23] F. Mancusi, A. Bochicchio, A. Laforgia, and F. Fruggiero, "Sustainability-Aware Maintenance for Machine Tools: A Quantitative Framework Linking Degradation Management with Life-Cycle Cost and Environmental Performance" *Applied Sciences* 15, no. 21: 11333 2025.

[24] D. Axinte, and N.Gindy, "Assessment of the effectiveness of a spindle power signal for tool condition monitoring in machining processes". *International journal of production research*, *42*(13), 2679-2691, 2004.

[25] P. J. M. Ali, R. Faraj, and S. Mohammed, "Data normalization and standardization: A technical report" Machine Learning Technical Report, vol. 1, no. 1, pp. 1–6, 2014.

[26] A. Maćkiewicz and W. Ratajczak, "Principal components analysis (PCA)," Computers & Geosciences, vol. 19, no. 3, pp. 303–342, 1993.

[27] M. Ritou, S. Garnier, B. Furet, J.Y Hascoët, "Angular approach combined with mechanical model for tool breakage detection by eddy current sensors". Mechanical Systems and Signal Processing 44(1–2), 211–220, 2014.

[28] Z.Y. Liu, M.P Sealy, W. Li, D. Zhang, X.Y. Fang, Y.B. Guo, Z.Q. Liu, "Energy consumption characteristics in finish hard milling". Journal of Manufacturing Processes. Journal of Manufacturing Processes;35: 500-507, 2018.

[29] Y. Joo, S. H. Oh, M. Cho and S. I. Kim, "Manufacturing information-based energy usage simulation for energy-intensive steel casting process". *Journal of Cleaner Production*, *379*, 134731, 2022.

[30] Y. Qin, X. Liu, C. Yue, L. Wang and H. Gu, "A tool wear monitoring method based on data-driven and physical output". *Robotics and Computer-Integrated Manufacturing*, *91*, 102820, 2025.