IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 28 April 2025, accepted 30 May 2025, date of publication 12 June 2025, date of current version 25 June 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3579204

SURVEY

A Systematic Review on Smart and Predictive Maintenance in Tool Condition Monitoring

DHANALEKSHMI PRASAD YEDURKAR, THOMAS SCHLECH, AND MARKUS G. R. SAUSE
Department of Mechanical Engineering, Institut für Materials Resource Management, Universität Augsburg, 86159 Augsburg, Germany
Corresponding author: Dhanalekshmi Prasad Yedurkar (dhanalekshmi.yedurkar@uni-a.de)

ABSTRACT The main goal in the field of reliability and maintenance is ensuring and enhancing the availability of assets. A decrease in the production capability of machines can be the outcome of untimely and inefficient maintenance planning. Unexpected and unscheduled machinery shutdown due to required maintenance reflects poorly on a business, resulting in damaged credibility and financial losses. This puts organizations in a position to decide between undertaking preventive replacement of parts that could have been used for some more time or running the machine till it dies (run to failure). On the other hand, organizations can improve their uptime by promptly replacing potentially good parts that could have been used for some more cycles. In addition to assisting enterprises in minimizing or preventing unplanned downtime, smart and predictive maintenance (SPM) extends the machinery's remaining useful life (RUL). A crucial instance is the cutting tool in machinery used for milling, drilling, or turning. It is an ideal asset to apply tool condition monitoring (TCM) since a breakdown of this part will result in unexpected downtime, resulting in a downturn in productivity. In a situation like this, a well-planned SPM strategy involving monitoring real-time health of tools used for cutting is beneficial. In the industrial predictive maintenance domain of Industry 5.0, accurate prediction of RUL of machinery is highly desired. Much research has been done on this topic, but none of it has covered all the techniques that have been used or have the potential to be used in the future. This study aims to support a comprehensive and methodical review of studies on the data-driven approach for estimating the RUL of cutting tools used in various computer numerical control (CNC) machining processes, including drilling, milling, and turning operations. This paper is a summary of various methods for monitoring, feature extraction techniques, decision-making models, and sensors currently available in this domain. A comparison of the accuracy of different prediction models used for estimating tool wear in TCM is also presented in this paper. The study concludes with a discussion of recent advances, challenges, and limitations in RUL prognostic methods that use artificial intelligence (AI), as well as the potential for further research in this domain.

INDEX TERMS Artificial intelligence, sensors, smart and predictive maintenance, tool condition monitoring, tool wear.

I. INTRODUCTION

In recent years, Internet of Things (IoT) has taken the world by storm. It allows one machine to communicate with another in real time over the Internet. In the industrial arena, one of the major applications of IoT is known as Industry 5.0. Presently, innovation is at the heart of a revolution in Industry 5.0, especially for people desirous of revamping organizational procedures in industry [1]. This has resulted in a huge surge in the use of Industrial Internet of Things (IIoT). In the domain of IIoT, industrial machinery is mainly driven by the use of sensors and sensor data, partly restricted to a local network only instead of the Internet. For any given industry, be it manufacturing, thermal, or automobile, it is data that makes the industry run, and it is possible for manufacturers to use this data to glean insights into their business. An example of such information would be making use of condition-based monitoring in the identification of a fault. Moreover, data can

The associate editor coordinating the review of this manuscript and approving it for publication was Agustin Leobardo Herrera-May.

be deemed to be a crucial asset when checking structurally used equipment in the business.

Nevertheless, in a majority of checks done in industries, identifying alert rules is not easy because of the complexity of procedures. Moreover, processes are dynamic. There is a possibility of a reduction in the total productive capacity of machinery by 5% to 25% because of deficient maintenance procedures [2]. Recent surveys reveal that unexpected or sudden equipment downtime because of breakdown can cost industrial businesses roughly $50 billion annually [3]. SPM has become one of the primary aims of Industry 4.0, and it relies on how remaining useful life (RUL) is predicted to a very great extent even as it tries to remain cost-effective.

Smart and predictive maintenance (SPM) is a cutting-edge maintenance methodology that benefits from various technologies and maintenance strategies, such as condition-based maintenance and predictive maintenance [4]. These methods apply to situations where profit and safety of facilities are enhanced by anticipating a failure and taking steps to prevent and mitigate its effects. SPM also attempts to preserve system functionality and behavior while guaranteeing efficacy and safety. Reducing expenses associated with maintaining industrial assets and unexpected services brought on by industry malfunctions and failures can prove to be very expensive. As a result, SPM technology should be included in regular maintenance for critically important business assets. Supervisors of operations and maintenance can obtain sophisticated information about the end-of-life of assets using this methodology. This enables manufacturers to budget ahead of time for system replacements or repairs, cut down maintenance expenses, and maximize asset uptime through automated system diagnosis and assessment.

Excellent and timely maintenance is essential, and as digitalization grows, more emphasis is being placed on utilizing data that is already accessible, making use of supporting technologies such as AI, machine learning (ML), digital twins, and big data along with the digital sector to pursue SPM. To maximize asset performance, an SPM system combines artificial intelligence (AI), specifically ML approaches for new dependability and maintainability, with integrated IoT. The use of SPM can be seen through the prism of organizational innovation to stay up to date with technological advancements made by manufacturing companies generally and maintenance organizations specifically.

A. CONTEXT ANALYSIS

SPM, which uses real-time data analytics to improve maintenance tasks and minimize operational disruptions, has become a crucial industrial asset management technique. Conventional maintenance techniques, like preventative maintenance (time-based servicing) and reactive maintenance (run-to-failure), frequently result in higher downtime, worse asset efficiency, and needless maintenance expenses. SPM, on the other hand, uses tool condition monitoring (TCM) methods, such as vibration analysis, acoustic emission, ultrasonic testing, thermal imaging, and oil analysis, to continually evaluate the health of the equipment to anticipate breakdowns before they happen. The emergence of digital twins, IoT, ML, and AI has greatly improved SPM by facilitating data-driven decision-making, predictive analytics, and real-time issue diagnostics [5].

In several high-reliability industries where operational safety and asset performance are crucial, TCM-based SPM has become widely used. SPM makes real-time engine health tracking possible in the aircraft industry, which aids airlines in planning maintenance schedules and preventing unplanned breakdowns that can endanger passenger safety [6]. Smart factories use AI algorithms and IoT-enabled sensors to monitor vital equipment, identify irregularities, and initiate maintenance before a breakdown happens [7]. By integrating condition-monitoring sensors into industrial robots and electric vehicles (EVs), SPM also helps the automotive sector by guaranteeing smooth production line operations. In the energy industry, TCM-driven SPM is used by wind farms and oil refineries for condition-based pipeline and turbine monitoring, which lowers expensive downtime and increases asset lifespan [8].

Despite its capacity to transform, SPM in TCM has several drawbacks. Because industrial assets are varied, data integration becomes complicated, necessitating sophisticated interoperability solutions. Financial obstacles may arise from the high upfront expenses of implementing AI-driven analytics, cloud computing, and smart sensors, especially for small and medium-sized businesses. Large-scale adoption is further complicated by the requirement for cybersecurity safeguards and industry-specific predictive models to protect critical operational data [9]. Innovations in digital twin simulations, federated learning (FL), and edge computing can help overcome these obstacles and improve SPM efficacy in industrial environments. SPM inside TCM is an essential step toward creating automated data-driven maintenance ecosystems, especially in light of the growing digital transformation across industries. The most recent approaches, difficulties, and prospects in SPM for TCM are examined in this evaluation, which offers information on how businesses can use cutting-edge technology to optimize asset dependability and operational effectiveness.

B. IMPORTANCE OF RESEARCH

The field of manufacturing is evolving very rapidly. TCM procedures, in particular, have advanced a great deal with the use of high speed machining tools and demanding workpiece materials with high hardness (>45 HRC) [10] or multi-material compounds. Sudden or unexpected breakdowns of tools can be costly to repair and have the potential to result in damage to the work environment harming the machine as well as operators [11]. Moreover, there is a growing need to implement research-backed solutions to assess the RUL of CNC processes. The estimation of RUL is considered a fundamental and challenging aspect of prognostics and health management of machinery and procedures. In this methodology, RUL is the most significant factor [11]. It enables predicting how healthy the current system is by constant indication of systems performance degradation and preventing unexpected breakdowns [12]. Concepts for RUL estimation also develop cost-effective solutions for maintenance that ensure that the considered systems are reliable [13]. As per ISO 13381, with the help of a method that is prognostic, manufacturers can calculate the risk as well as the time of system breakdowns [14]. RUL is predicted by analyzing the past operation status of the equipment as well as the present condition. In today's competitive economic climate, such estimation of RUL is often necessary [15]. Numerous critical applications, such as required components of machinery, airplanes, nuclear power plants, and so on, find RUL estimation very advantageous. It is possible to determine the useful life of machinery using traditional methodologies. However, such approaches only factor in the static conditions of the equipment. With the industrial evolution leading toward the age of Industry 5.0, it is possible to estimate RUL of systems during operation with the help of real-time monitoring. RUL is a key target in condition-based maintenance [16], [17]. In fundamental terms, RUL can be defined as the period from the present time to the end of the functional lifespan of a given product [13]. Such prediction of RUL is beneficial when checking the operational functioning of machinery, managing inventory, planning maintenance schedules, and so on.

As per predictions for the years 2021 to 2026, maintenance of prescriptive and predictive nature will cost the industry around \$22.72 billion by 2026 with a compound annual growth rate of 19.68% [18]. For every type of business, as per a survey, the average cost of equipment downtime is about \$260,000 per hour [19]. Due to ignorance of RUL estimation, it is said that about 70% of industries are unaware of their own machinery replacement or maintenance schedules [20]. In the manufacturing sector, about 20% of equipment downtime results from a breakdown in the cutting tool. The selection of an appropriate maintenance plan and a well-thought-out estimation of the useful life of equipment minimizes unexpected downtime. Monitoring systems carefully and accurately will raise productivity by 10-40% along with a cost saving of up to 40% [21].

C. EVOLUTION AND MOTIVATION OF STUDY

As a result of the significance coupled with the pressing demands of TCM in practical machining, in-depth research has been undertaken in this field. This has resulted in a large volume of academic material over the past half-century [22]. In Figure 1, TCM numbers have been published on the basis of a search from the Web of Science, and these numbers show a rising trend [23]. A few in-depth and comprehensive review papers have been written as part of these publications. The papers analyze fundamental tenets, primary technologies, and TCM applications used in industry from various perspectives.

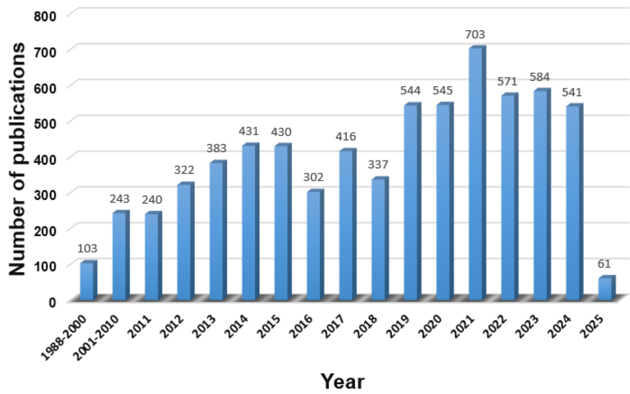

FIGURE 1. Trend of literature in RUL-based TCM prediction.

Walter et al. [22] worked on researching TCM as part of RUL, where the authors studied the workability of a telemonitoring model. In the two decades from 1960 to 1980, intensive research was conducted in feasibility [23], mechanism [24], and the hardware layout of vision-based condition monitoring. During the 1990s experiments were increasingly conducted to investigate degradation behaviour. Such experiments revealed a correlation between wear of machining tools and the machined surface texture [25], the feature characterization making use of light scattering patterns [26], and the correlation between chatter marks and features of the machined surface texture [27]. Since the start of the 21st century, numerous studies have focused on improving hand-coded feature extraction methods used for selecting and making decisions (i.e., classification and regression). The last few years have seen a rise in the emergence of concepts used in industry, such as big data and intelligent manufacturing. These concepts have resulted in numerous sensors being brought into use in the process of manufacturing. These sensors generate a large volume of data with sparse and high-dimensional fault or information on degradation. When data characteristics become complicated and processing conditions change frequently, it is tough to use hand-coded features to represent these tasks. Due to these disadvantages, researchers worked on studying and developing techniques that use intelligent data-driven methods that use AI [28]. The study charts the development of texture representation over two decades, emphasizing techniques like convolutional neural network (CNN)-based approaches, gabor filters, and local binary patterns (LBP), which are currently essential to TCM for tool wear analysis.

Recently, there has been a shift in the focus of the research from conventional ML to deep learning (DL).

The work in [29] was the primary ground-breaking basis of the use of TCM methodologies in industrial applications. According to the study, a machined surface texture can reveal information about machine quality and tool wear. Using image processing techniques, the study analyzes surface roughness, a crucial sign of tool deterioration. One of the main objectives of SPM in TCM is to help manufacturers prevent machine breakdowns, and the research supports the notion that surface quality analysis can act as an early predictor of tool wear.

The study undertaken in [30] detailed implementation of machine vision sensors and digital image processing methodologies in TCM. The authors of [29] were the first to use the newest innovations in machining monitoring even as they worked with sensor fusion techniques and reconfigurable sensor applications in industrial procedures.

The authors in [31] detailed the development of a system to monitor processes that were based on AI approaches along with specific instructions on implementation. Authors of [32] investigated sensing methods, signal processing, and decision algorithms of TCM for various machining procedures. Authors of [33], [34], and [35] investigated drilling, turning, and milling machining, respectively. The study undertaken in [36] and [37] underlined the advantages of artificial neural networks and wavelet transforms when used in TCM. DL methodologies, along with their basic theories and application cases, have been depicted methodically in [38] and [39]. The authors have also tried to investigate new possibilities for TCM within the framework of industrial big data.

The study in [40] and [41] focused on existing challenges TCM faced in model performance and data processing along with possible solutions. When using TCM procedures, accurately estimating tool life is crucial to optimize the functional life of the cutting tool. To avoid unexpected or sudden downtime, it is essential to implement maintenance strategies that are applicable to undertake non-stop, real-time monitoring of the cutting tool. In recent times, advancements in sensor technology and cutting-edge AI methods have provided in-depth data about the health of the milling machine. Data-driven techniques for predicting RUL during milling were reviewed comprehensively in [40] and [42].

The study described in [43] makes use of machine data that already exists, removing the need for more sensors. It has also been verified in actual production settings, improving product quality and encouraging zero-defect manufacturing. In [44], a sensorless monitoring system that detects tool wear while dry, high-speed milling for aerospace aluminum alloys using internal machine signals is evaluated. The method seeks to detect wear patterns by examining these internal signals without extra external sensors, which would streamline the monitoring procedure and save expenses. The study in [45] introduces a data acquisition system that can capture cutting forces and the positional coordinates of the cutting tool at the same time while complex shapes are being milled. The method solves typical problems in milling experimentation, including correctly linking force data to particular machining places by connecting the cutting forces with precise tool positions. This improves analysis and optimizes the milling process. During machining experiments, the authors of [46] present a technique for simultaneously monitoring cutting forces and the exact location of machine tools. Understanding the link between tool position and the forces experienced during cutting operations allows for a thorough examination of the machining process, improving diagnostics and optimization. These studies collectively advance manufacturing processes by combining digital technologies and real-time monitoring, by increasing productivity and product quality.

This study aimed to introduce the readers to feasible predictive maintenance methods. The following are the primary contributions of this study: A review of the existing literature on this subject has shown that very little in-depth research has been conducted on sensors, algorithms, and monitoring techniques for RUL estimation utilizing a data-driven approach. The lack of model diversity, precise construction rules, and industry-specific applications in ML for condition monitoring study published in [1] makes practical implementation difficult. Furthermore, it ignores time and cost limitations, essential for realistic implementation. High upfront costs and unpredictability in monitoring device reliability are highlighted in the study in [2], indicating the need for more robust and affordable condition-based maintenance systems. This analysis also covers advancements in RUL and the direction of this field in the future, which will encourage researchers in the fields of prognostics and health to look at data-driven methods for forecasting RUL of vital equipment. This study extends the limits of SPM in machining by integrating FL, physics-based modeling, and data science. This study also helps close the gap between AI research and practical application by: i. using contemporary methods like physics-based AI to improve data-driven TCM; ii. using FL to ensure AI privacy and scalability; and iii. discussing the best ways to improve SPM explainability using data visualization techniques like interactive dashboards. Manufacturers can use these technologies to boost productivity, lower failure rates, and move toward completely self-sufficient Industry 5.0 systems.

This paper provides a comprehensive step-by-step survey on the topic of data-driven RUL estimation for cutting tools used during drilling, milling, and turning. Table 1 lists research questions the proposed study tries to answer by this comprehensive survey in the field of data-driven RUL estimation.

D. ORGANIZATION OF THE PAPER

The significance of the study, its evolution and motivation, its goals, and research questions have been outlined so far. The research methodology is described in section II, along with selection criteria, selection outcomes, and quality analysis. Background information about TCM measurement techniques, machining events, and SPM is provided in Section III. The general TCM process flow for CNC machining is described in Section IV. RUL data-driven decision-making methods are discussed in section V. The role and significance of big data in smart TCM are described in section VI. Section VII offers suggestions for more research. It also provides the paper's conclusion at the end.

TABLE 1. Research questions and approach taken to address the questions.

	Research Questions	Approach	Importance and scope	Discussion carried out in the respective sections
RQ 1	Smart and predictive maintenance: what, why, and how?	Various strategies utilized in industry are studied and summarized	It entails employing multi-sensor data, AI, and signal processing to evaluate and predict real-time tool wear and failures to maximize tool performance, reduce downtime, and increase efficiency	III
RQ 2	Which sensors can be utilized to gather information during ? machining?	Different sensor types and their usage are examined	Many sensors, such as force, vibration, acoustic emission, temperature, motor current, can record detailed machining data, allowing precise TCM and process optimization	III and IV
RQ 3	How can the data be gathered and combined from different types of sensors?	A study considering various TCM processes and different types of sensors used to acquire the data	Precise evaluation of TCM is made possible by collecting data from several sensors utilizing synchronized data gathering systems and integrating it using sensor fusion techniques	III and IV
RQ 4	Which algorithms are used to predict the RUL of the cutting tool?	Studies about various RUL algorithms are considered and discussed	ML techniques and more sophisticated approaches like deep learning and survival analysis are frequently used algorithms to estimate the RUL of cutting instruments	IV, V and VI

II. RESEARCH METHOD

Since the field of estimating RUL is very broad, the authors undertook a systematic literature survey using a methodical review procedure to respond to the research questions. The current study takes into account the following criteria to assure the caliber and applicability of the chosen research articles in the fast developing field of AI approaches in RUL estimation: i. reputable conferences and journals such as IEEE, ACM, and Elsevier are taken into consideration, as are highly reputed universities such as MIT or Stanford and leading companies such as Google or Siemens; ii. since AI is developing rapidly, include papers published within the last three to five years; and iii. confirm the datasets and methodology used aligning with current best practices; articles that include case studies or real-world applications in sensor data processing, anomaly detection, or predictive maintenance.

The methodology has been divided into three sections: selection criteria, query results and content assessment.

A. SELECTION CRITERIA

For the purposes of retrieving pertinent documents, the databases that the authors used, were Science Direct, Scopus, Web of Science, ACM, Springer, IEEE and PubMed. A specialized query or search string was made up to extract related research articles, using numerous database searches. Table 2 lists the search string or query that was executed to look up a number of documents. This was done by enjoining the master, primary, and secondary keywords and also using the Boolean operator AND. A well-thought-out search strategy is necessary to guarantee a thorough but objective retrieval of pertinent TCM literature. To gather all the relevant studies without overlooking important research and to avoid irrelevant or biased results that could skew the review, entails improving boolean operators, keywords, and filtering strategies. The search query was carefully refined using boolean operators (AND, OR), which ensured a balance between specificity and inclusivity. By removing pointless research on TCM in non-machining domains such as robotics or electrical systems, the AND operator guarantees that studies address TCM only in machining procedures. The OR operator ensures more complete information by capturing various terminologies used across fields. Integrating conventional TCM research with contemporary AI-driven methodologies is ensured by combining domain-specific and AI keywords. It includes both traditional monitoring methods and contemporary AI-based strategies, such as Tool wear'' OR ''Sensor'' OR ''Artificial Intelligence'' OR ''AI'' OR ''Machine Learning'' OR ''ML'' OR ''Decision-Making Model'' OR ''Data Driven Model'' OR ''Predictive Maintenance''. To retrieve the best-ranked web pages, research papers, and white papers, snowballing methodologies were applied.

B. QUERY RESULTS

Snowballing is a method for conducting a literature review in which more pertinent papers are chosen by looking through a research article's citations (ahead snowballing) and references (reverse snowballing). Combining database search and snowballing improves the search method and increases the quality and coverage of the literature [41]. An initial seed of 18 articles was used to apply the snowballing approach. There were four iterations of the snowballing process. In the initial iteration, 35 articles, out of which 33 from forward snowballing and 2 from backward snowballing, were obtained. After applying inclusion/exclusion criteria to these 35 records, 23 articles were ultimately chosen for the following iteration. There were 23 articles in the initial seed for the second iteration. 82 articles were retrieved using the forward snowballing method (68 articles) and the backward snowballing method (14 articles). Fifty-three were chosen for the following iteration upon the completion

TABLE 2. Terms that are included in the search string (query conducted).

Keywords	Search String
Master	("Tool Condition Monitoring" OR "TCM")
Primary	(Milling OR "Milling Operation" OR "Milling Process") AND TITLE-ABS-KEY ("Turning" OR "Turning Operation" OR "Turning Process") AND TITLE-ABS-KEY ("Drilling" OR "Drilling Operation" OR "Drilling Process")
Secondary	("Tool wear" OR "Sensor" OR "Artificial Intelligence" OR "AI" OR "Machine Learning" OR "ML" OR "Decision Making Model" OR "Data Driven Model" OR "Predictive Maintenance")

of the inclusion/exclusion criteria. The snowballing process was completed after the third and fourth iterations, which produced 102 and 41 articles, respectively. The snowballing process yielded a total of 219 articles.

After examining publications using multiple databases (Science Direct/Scopus-181, ACM/Springer/Web of Science-101, and IEEE-21) through 2025, 303 records were identified. Repetitive articles from the various databases were excluded (N = 28). To ensure methodological consistency, specificity, and relevance, some studies, such as those that concentrated on electrical parameters, gears, and pumps, were not included in the thorough assessment of TCM in this study. Exclusion involves the following implications: i. concentrating only on machining-related TCM techniques, improves relevance; ii. reduces diminution of conclusions with insignificant approaches that might not directly pertain to cutting tool degradation; iii. maintains an exclusive focus on direct tool wear indicators instead of indirect machine-level factors; and iv. excluded investigations might employ different performance indicators, such as current deviation of motors and oil particle count of gears, making cross-comparison challenging. Additional documents were also omitted, such as examples unrelated to drilling, milling, or turning, work involving electrical parameters like motor power, and records about gear boxes, pumps, wind turbines, shafts, and bearings (N = 61). Finally, after removing documents, 219 key documents related to TCM RUL estimate were considered for the study.

C. CONTENT ANALYSIS

The authors have compiled a short list of the chosen published papers. As per the research questions, an appropriate maintenance plan is required to be examined, which can be applied effectively to attain the research goal. This paper includes the following points based on the short-listed papers for quality analysis.

(i) SPM: emphasis was given by the research work to the various predictive maintenance approaches that are used in industry;

(ii) Sensors: research was also undertaken to investigate the various sensors that are utilized in the milling machine for gathering data;

(iii) Data-driven RUL model: this paper primarily focuses on data-driven methodologies for estimating RUL in TCM procedures such as milling, drilling, and turning;

(iv) Decision-making algorithms: another area on which the paper focuses is the various algorithms that are utilized to make decisions in the estimation of RUL;

(v) Advancement in RUL Prediction using AI: the published papers also have shed light on AI-based methods that can be applied to estimating RUL exactly and robustly.

An unbiased screening framework was used to conduct the review evaluation to enhance the caliber, dependability, and transparency of the articles chosen. The procedure integrated inter-rater reliability (IRR) evaluation with systematic screening procedures, such as preliminary keyword-based screening, abstract and title examination, and full-text suitability evaluation, all directed by predetermined inclusion and exclusion criteria. Structured consensus techniques were used to settle disagreements found during the review. This method significantly reduced subjectivity, lessened selection bias, and improved the rigor of the synthesis of the literature. Therefore, the final selection provides a fair summary of current developments in SPM in TCM research.

III. BACKGROUND RESEARCH

An in-depth survey on the different techniques to measure TCM has been undertaken in this study to develop a systematic review of the existing literature, which is discussed in the following sections.

A. TCM MEASUREMENT METHODS

Systems for keeping track of conditions can be used in real-time, online, inline, and offline. While undertaking TCM, the primary distinctions between online and real-time need to be considered, including those related to latency, processing, decision-making, and reliance.

Online systems function rather slowly, gathering and processing data regularly, frequently utilizing cloud-based solutions to gain predictive insights. On the other hand, real-time systems process data quickly, allowing for prompt decision-making, typically at the edge or via local computing. While real-time systems are essential for prompt reactions, like emergency shutdowns or safety measures, online monitoring is utilized for trend analysis and long-term optimization. Online systems evaluate data over time, whereas real-time systems operate within milliseconds. This is the main difference between the two types of systems. The research mentioned in [47] offers a thorough strategy to improve condition monitoring in broaching operations.

The methodology combines offline tool wear examinations with real-time monitoring, using motor drive consumption data, load cells to quantify cutting forces, and accelerometers to record process vibrations. This combination reduces production errors and increases overall process efficiency by enabling the early diagnosis of tool damage.

Using inspection tools like an optical microscope to assess tool health at random intervals is a TCM system offline method, as it requires stopping the machining operation [5], [47]. In contrast, the machining process is unaffected by online TCM systems, where the tracked parameters are recorded at distinct intervals and linked to the tool state at predetermined intervals. There are no restrictions on the duration of the acquisition intervals or the time required to process the collected data to initiate corrective measures [47]. With minimal latency, real-time TCM systems constantly gather and process data at precisely controlled intervals without stopping the machining operation. This makes establishing preventative measures against cutting tool malfunction and workpiece damage feasible. It can also be used as an adaptive control mechanism to implement dynamic tool compensation, enhancing machining process accuracy and economy [48]. Nevertheless, it requires a relatively short interval for obtaining and analyzing the tracked signals and forecasting the state of the tool's health, resulting in the application of low-cost computational algorithms [47].

A typical real-time TCM system comprises four stages: signal acquisition, pre-processing, feature extraction, and selection, and a requisite tool health model.

Initially, the system undergoes offline training to establish the correlation between the signals and predictive features of the chosen sensors. Subsequently, picked sensors and features are employed to determine the degree of tool wear via real-time system implementation. Based on the tool health state, corrective measures involving changed cutting federate, optimization loops, or tool change, including the possibility for regrinding of a worn tool, are carried out. The information can be classified into two types based on their measurement methods: direct and indirect, as shown in Figure 2 [49].

Using machine vision [50], and optical microscopy [51] to precisely assess tool wear is generally reliable. Regardless, because of the challenging environment of machining processes and the necessary process pauses to determine the tool health state, they are not as practical, efficient, or economical as the indirect methods [52]. Moreover, any unanticipated cutting tool wear, such as chipping and/or breakage while the tool/workpiece is involved, cannot be detected by direct techniques. Consequently, indirect measurement methods have been established for real-time monitoring so that prompt action can be taken when required.

The techniques above are associated with a tool health state with supplementary parameters that are measured, like cutting forces, torque, vibration, acoustic emission, and power signals. Although indirect measurement methods are applicable and cost-effective, they are less accurate than the direct methods and the signals they generate are noisy due to varying process parameters and the machining environment. Therefore, to improve the reliability and to indicate the health state of the tool precisely, characteristic features extracted from the obtained signals using advanced signal processing techniques are necessary. As a result, TCM is more dependable and robust, and helps prevent false alarms and general malfunction of process control methods.

Also, in TCM, the presence of a coolant greatly impacts sensor readings, variations in chip flow, and machine tool dynamics. A coolant can change temperature readings, reduce vibrations, and change acoustic signals, which could cause tool wear or defects to be misinterpreted. Uneven force fluctuations brought on by variations in chip flow produce erratic vibration and acoustic signals, which makes anomaly detection more difficult. The accuracy of condition monitoring models is impacted by changes in sensor data introduced by machine tool dynamics, such as spindle performance, structural vibrations, and thermal expansion. It is essential to comprehend and account for these elements to enhance tool life estimation and predictive maintenance.

With the advancement of sensing and industrial big data, multi-sensor fusion technology has become popular for TCM. Uncertainties in the decision-making process of the monitoring system might arise from time-varying cutting process elements such as tool wear and machine vibration. To increase monitoring accuracy and robustness, the multi-sensor fusion technique seeks to reflect tool state changes through complementing information fully. The kind and quantity of sensors, and the fusion strategy are critical factors in the effectiveness of multi-sensor fusion approaches. It should be noted that not all sensor types are appropriate for the fusion approach. For instance, force and vibration data or force and current/power are comparable, and combining them does not affect increasing the monitoring accuracy. In the TCM work, accuracy, sensitivity, reliability, complexity, non-intrusiveness, and real-time performance must also be considered. The effectiveness of the various sensors monitoring these factors is shown in Table 3. All things considered, the AE and current perform better than the other sensors.

Two approaches have been proposed to model the tool health state in TCM systems: i. models that are data-driven; and ii. models based on the laws of physics. Mechanistic models or semi-empirical laws are often employed in physics-based models to facilitate the cutting processes [53]. They offer an understanding of the inner principles of the machining process and can operate in a-priori untested machining scenarios. However, owing to the intricate and nonlinear characteristics of the cutting process, several factors can hardly be addressed thoroughly, such as the lubrication conditions and cutting temperature, which reduces the precision of the prediction [47]. Given this, physics-based models that have been proposed in literature, like the generic tool wear model [53], the Taylor model [54], and many

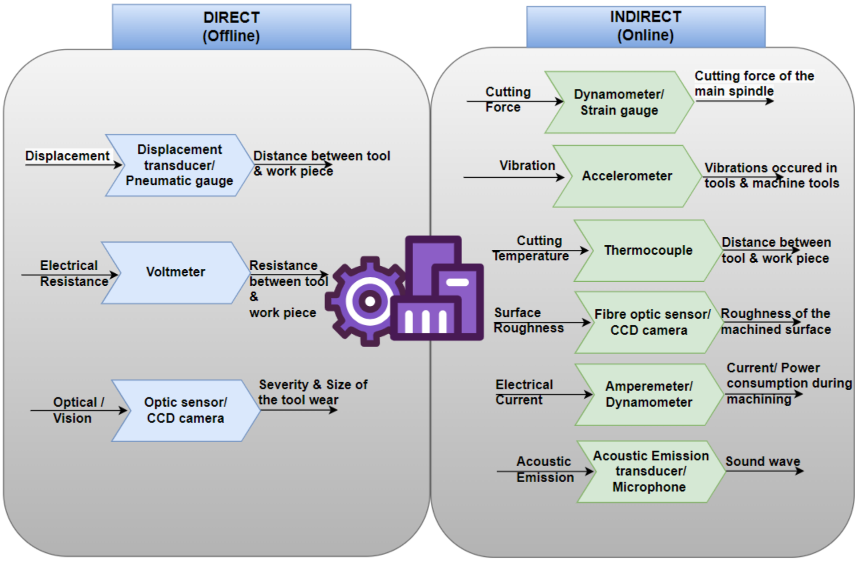

FIGURE 2. Types of tool condition monitoring.

TABLE 3. Qualitative evaluation of several TCM techniques according to significant performance factors.

TCM Approach	Accuracy	Sensitivity	Reliability	Complexity	Non-intrusive	Real-time analysis capability
Vibration analysis	High	High	High	Medium	High	High
Force sensors	High	High	High	Medium	Low	High
Acoustic Emission	High	Very High	Very High	High	Very High	High
Thermal imaging	Medium	Medium	Medium	High	Very High	Medium
Machine Vision	High	High	Medium	High	Very High	Medium
AI-Based SPM	Very High	Very High	Very High	High	Very High	High

more [55], cannot‘ be used to accurately predict tool wear in real operation conditions.

Advanced machining aims to optimize the entire process by maximizing the machine's capabilities to reduce production costs, increase output, satisfy pre-established component quality standards, and improve tool life. It includes ongoing offline or online optimization of the cutting speed, feed rate, and strategies. To handle this ongoing variability with the least amount of calibration work and minimal process disruption, a real-time autonomous TCM system with an excellent generalization and robustness is desired.

B. TOOL EVENTS IN MACHINING

Developing an advanced machining process requires a greater focus on the variables that affect the process and its ultimate results, including surface roughness, tool breakage, progressive wear, and breakdown. A significant enhancement in the efficiency of machining operations may be attained by reducing the impact of various variables that deteriorate the condition of tools. To lower their impact, it is essential to be familiar with all the specifics of uncertain events occurring during machining.

The essential events inextricably linked to machining that minimize the productivity of cutting tools are tool wear, tool breakage, chip formation, chip breakage, chip removal, and tool breakdown. Various factors can cause a tool to malfunction, as shown in Figure 3. An approximate estimate of the frequency of occurrence for each significant tool event is provided in Table 4. Both the process and the tool condition are specifically impacted by the phenomenon as a whole. Additionally, they may have an abrasive, thermal, chemical, or mechanical impact on the tool. A detailed description of the mechanism of tool wear during metal cutting, including steel, polymers, and aluminum alloys, and its associated effects, has been provided in [55].

Tool wear is a gradual failure process that usually consists of the most common wear mode, which is determined by the geometry of the tool insert, the surface of the workpiece and tooling material, and the cutting demands. Tool wear advancement for a given cutting tool and workpiece material amalgamation may depend solely on the cutting conditions, primarily the undeformed chip thickness, cutting speed, and a mix of various wear mechanisms. The swept area increases dramatically as the depth of the cut increases, dramatically reducing the tool life. The leading cause of tool wear at minimal cutting speeds is the cutting point rounding off, resulting in a sharpness loss. With abnormally high values causing plastic flow at the cutting point, the wear-land pattern adjusts to the resulting change as the cutting speed rises. The two primary wear processes at low cutting speeds include

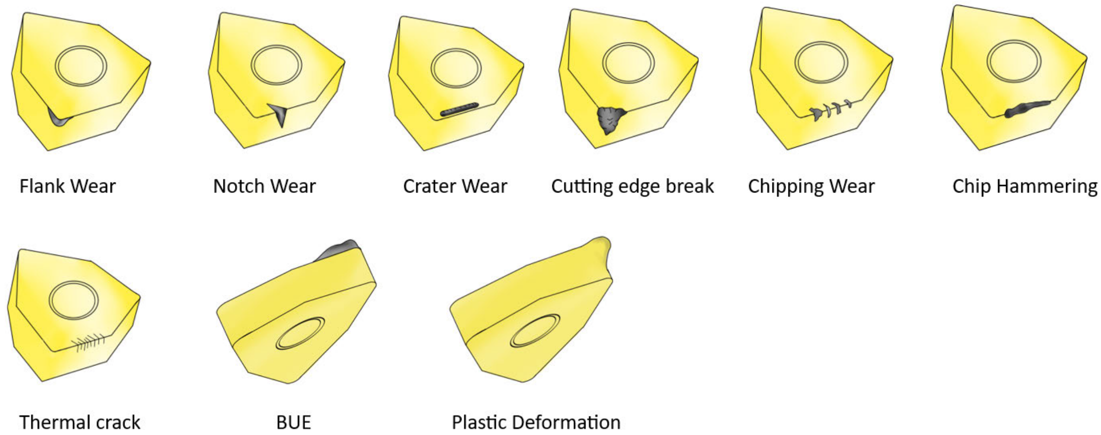

FIGURE 3. Typical tool wear patterns [55].

TABLE 4. Estimated occurrence rates of various tool wear and machining damage mechanisms.

Event	Description	Estimated occurrence
Flank wear	Wear on the tool flank over time as a result of sliding contact with the material, which results in a rough surface	Hours to Days
Notch wear	Wear is caused by abrasive particles and work-hardened materials at the depth of the cut zone of the tool	Minutes to Hours
Crater wear	High temperatures and chemical diffusion cause wear on the rake face, which impairs cutting efficiency	Hours to Days
Cutting edge break	Abrupt and total edge breaking brought on by impact loading, incorrect tool geometry, or excessive force	Milliseconds to Seconds
Chipping wear	Impact forces or hard components in the workpiece can cause minor fractures along the cutting edge	Seconds to Minutes
Chip hammering	Occurs when chips hit the tool surface repeatedly, creating micro-fractures, which are prevalent in drilling and turning	Seconds to Minutes
Thermal crack	Causes carbide tool cracks (which are typical in interrupted cutting) as a result of cyclic heating and cooling	Minutes to Hours
Built-up-edge (BUE)	Tool performance is impacted when workpiece material sticks to the cutting edge (which is typical in delicate materials like aluminium)	Minutes to Hours
Plastic deformation	The tool becomes softer and permanently deformed due to high heat and pressures (observed in high-speed machining)	Minutes to Hours

adhesion and abrasion. High cutting speeds are necessary for abrasion and chemical wear, mainly when chip formation is ongoing [56].

C. SMART AND PREDICTIVE MAINTENANCE

Smart maintenance in Industry 5.0 encompasses all the organizational and technical measures taken to utilize digital tools to enhance the efficiency of servicing and maintenance, which, in turn, creates greater value for the organization. At the heart of smart maintenance is the gathering and linking of data from various equipment, buildings, and plants. Sensors are installed in the technical infrastructure to measure the performance and functionality of the equipment. The data gathered by the sensors is forwarded to the various digital or software applications or, in a more advanced setup, to a central application platform.

The function of SPM is to recognize any indication of damage or wear and tear in different parts of the equipment as soon as possible to prevent sudden and unexpected breakdowns. SPM involves continuous monitoring as well as analyzing of all the assets of an organization, which allows the organization to predict and take notice of possible breakdowns. Moreover, it generates data on the planning of maintenance and spare parts and automates maintenance. Multiple parameters such as temperature, energy consumption, vibration and others are monitored and measured by sensors installed in the equipment so that active operations can be monitored. In case of deviations from the norm or indications of possible problems or breakdowns, alarms are triggered by the system so that countermeasures can be implemented to avoid a breakdown. Despite such awareness and need, most of the systems available in the market for monitoring are proprietary solutions that work in isolation and only keep track of the conditions of individual parts.

1) BEYOND PREDICTIVE MAINTENANCE

There are three ways in which SPM extends beyond mere predictive maintenance:

i) Monitoring: A wide network of various assets can be monitored by SPM when IoT connects them. It becomes easier to manage the integrity of all the equipment using one dashboard when the assets are all linked together. Moreover, a lot more data points are generated by a network than by individual machines. By creating a combination of operational technologies and network data, it becomes possible for maintenance professionals to discover patterns that exist between equipment breakdowns and utilize an ML platform that enables optimization or enhancement of prediction algorithms over some time;

ii) Automated maintenance: It is possible to automate a few of the maintenance tasks with the help of SPM. Moreover, predictive maintenance can forecast possible machine failures. However, SPM extends further, and it can automate a few of the maintenance tasks, making use of cognitive data processing techniques. For example, if in case an inherent fault in the equipment is detected, SPM raises a red flag and issues a maintenance order. Next, it assigns a technician to address the issue, and schedules a ticket for a Computerized Maintenance Managed System. If any parts need to be replaced, SPM checks the spare parts inventory and replaces the faulty part in an Enterprise Resource Planning (ERP) system and includes it in the work order. If the spare part is not in stock in the inventory, SPM creates a purchase request in the ERP system. This request needs to be approved by the procurement specialist; and

iii) Implementation: Integrating SPM into other maintenance management systems. For the automation of specific tasks, the predictive maintenance platform should be included with either the ERP, or manufacturing execution system (MES). It is possible for conventional predictive maintenance to cause significant overhead if it is not incorporated into daily maintenance processes of an organization. A combination of SPM and other maintenance systems helps develop both, a sustainable platform for the procedures and the possibility of automating the maintenance procedures over a period of time.

2) STEPS TO SPM

As a rule of thumb, a pilot phase should be undertaken on one production line or on one or two assets that are well-suited. Figure 4 depicts the five steps to obtain SPM as proposed in [56]. To start with, just the first two steps, namely Asset Monitoring and Health and Condition Monitoring can be covered. It is difficult to move straight on to predictive maintenance because it takes a bit of time to put data collection procedures in place. A very significant point is that the equipment has to fail a few times, at least, or alternately it has to exceed the defined tolerance limit in order to apply and verify the algorithms. The prediction models will become more experienced in accurately predicting the more frequently a machine fails over a given period of time. It is possible to optimize error thresholds once adequate error information has been gathered reliably. With such data in hand, statistical analysts can come up with predictive models. Machine availability and uptime can be raised by 20% to 30% with predictive maintenance. It becomes easier for an ML platform to monitor failure information and enhance algorithms if more errors occur. This helps enhance the forecasting ability for each breakdown and minimizes sudden and unexpected downtime. Maintenance planning can prove to be significant in improving the efficacy, safety, quality, and throughput of an organization. Moreover, cost of maintenance and spare parts inventory can be brought down.

Data-driven decision-making is made possible by SPM, which can also lower costs, boost safety, optimize maintenance schedules, and improve reliability. Organizations can utilize SPM to anticipate malfunctions in equipment, schedule maintenance proactively, and prevent unplanned breakdowns by using cutting-edge technologies and data analytics. This strategy prolongs the life of the equipment, reduces the need for emergency repairs, and minimizes downtime. Prompt action to avert significant failures is ensured by early detection of irregularities by continuously monitoring and evaluating the health of the equipment [56]. The primary principle of SPM is to diagnose, come up with a prognosis, and analyze the signals that have been captured by the sensors [57]. The main purpose of SPM is to raise productivity and quality due to a reduction in the cost of maintenance and downtime.

Figure 5 depicts the diagnostics and prognostics framework to calculate RUL of the components. Authors in [56] categorize RUL prediction into four steps:

i) Fault detection: detecting abnormal conditions;

ii) Fault isolation: identification of which component is failing;

iii) Fault identification: estimating the nature of the fault; and

iv) RUL prediction: predicting lead time to failure.

IV. OVERALL PROCESS FLOW OF TCM IN MACHINING PROCESS

The foundation for achieving an intelligent TCM using an SPM system in machining is sketched in Figure 6. This framework supports real-time process optimization and quality control and it offers a feedback prediction of the tool condition according to analytical and sensor-based models. With the huge number of studies, enormous efforts are being made to establish new approaches, and cutting-edge technologies are being put in place in order to enhance TCM system performance and offer solutions to problems that manufacturers encounter.

A. DATA SOURCES

The development of highly sensitive, accurate, and dependable techniques—which can be divided into ‘‘direct’’ and ‘‘indirect’’ methods—is required to monitor tool wear and failure. For precise, dependable, and real-time tool wear prediction, fault detection, and RUL estimate, the types of sensors used in TCM are crucial. The selection of sensors is based on their capacity to record high-quality data pertinent to machining operations while conforming to the most recent developments in Industry 5.0 and TCM.

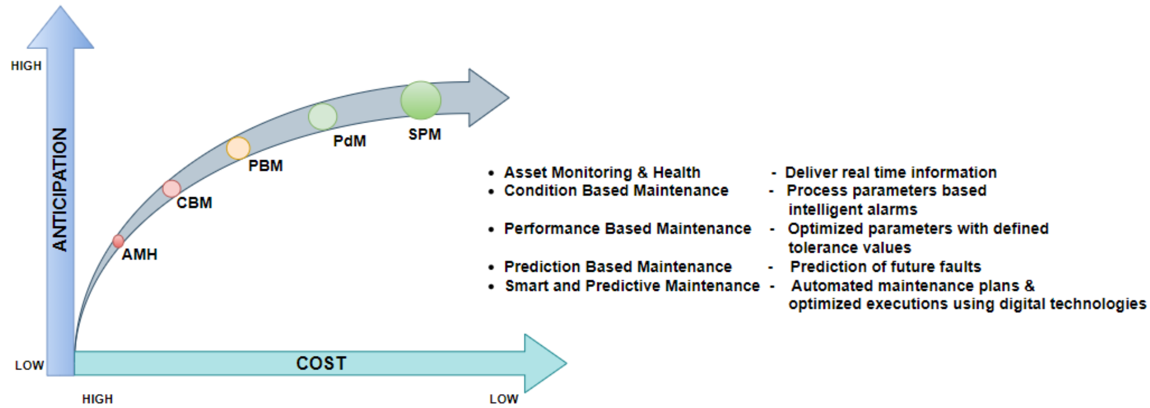

FIGURE 4. The method to achieve SPM as proposed in [56].

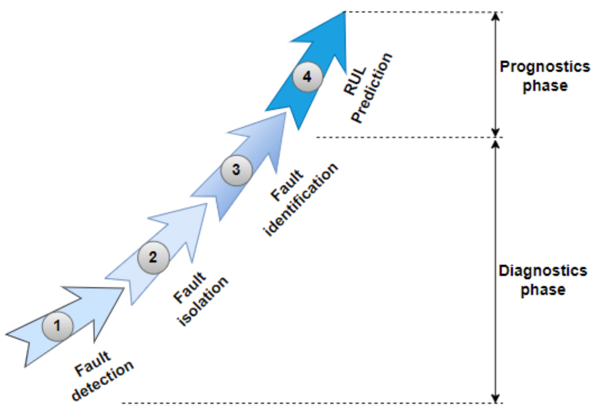

FIGURE 5. The four steps for RUL prediction.

The following justifications support the choice of sensors in TCM: i. In practical machining, the selected sensors successfully record tool wear patterns. ii. They complement applications for digital twins, DL, and contemporary AI. Meanwhile, the selected sensors have specific qualities that fit the TCM selection: Acoustic and vibration sensors are the best for measuring tool wear in real-time and identifying problems early; Force sensors are excellent for force-based wear analysis and adaptive machining; Temperature sensors are useful for predicting wear caused by heat, while vision-based sensors are best suited for AI-based tool wear image analysis.

1) INDIRECT APPROACHES

As previously mentioned, indirect approaches are preferred as real-time tool health gauges as they create a relationship between the tool health state and the measured process parameters. In TCM systems, cutting forces [58], vibrations [59], acoustic emissions (AE) [60], and spindle motor feedback signals [61] are examples of frequently observed indirect parameters. Although they are less practical for use in industrial settings, additional parameters like the spindle rotation speed and cutting-edge temperature [62] can also be monitored to determine the health state of the tool. The standard method involves attaching the required sensors to the workpiece or spindle.

The following subsections explain indirect TCM measuring techniques. Here, the TCM factors taken into account are feed rate F_n, cutting depth a_p, and cutting speed V_c.

a: CUTTING FORCE SIGNAL

The force of the cutting signal is the most frequently used signal for identifying tool wear because of its high degree of sensitivity to tool conditions and its status as the most stable and reliable parameter in machining processes [63]. The cutting tool turns dull and its sharpness is reduced as the machining process passes on. This increases the friction force between the tool and the workpiece and the cutting force required to eliminate chips coming from the material of the workpiece under similar cutting circumstances [64]. The rise in cutting forces may additionally be linked to various other aspects, such as the cutting conditions, the material of the cutting tool, and the material of the workpiece.

Considering that the thermal softening process outcompetes the strain hardening effect, the cutting force may not increase for hard-to-cut materials like Ti6Al4V beyond a certain point. The TCM system may raise a false alarm when it operates in different cutting conditions. If the sensor bandwidth being used is sufficient to cover the chatter frequencies, cutting forces may also be applied in chatter detection [65]. Because of its high sensitivity and dependability, the table dynamometer is a highly used sensor for force measurements in indirect TCM adjustments in educational institutions. It is positioned beneath the machined part, allowing it to detect minimal changes in load. However, because of its high cost and the requirement for protection from overload, it is unsuitable for application in manufacturing environments [66].

Additionally, the table dynamometer lowers the rigidity of the machining unit and limits the dimension of the machined part. One way to improve the practicality of this technique for use in industrial settings and address most of its shortcomings

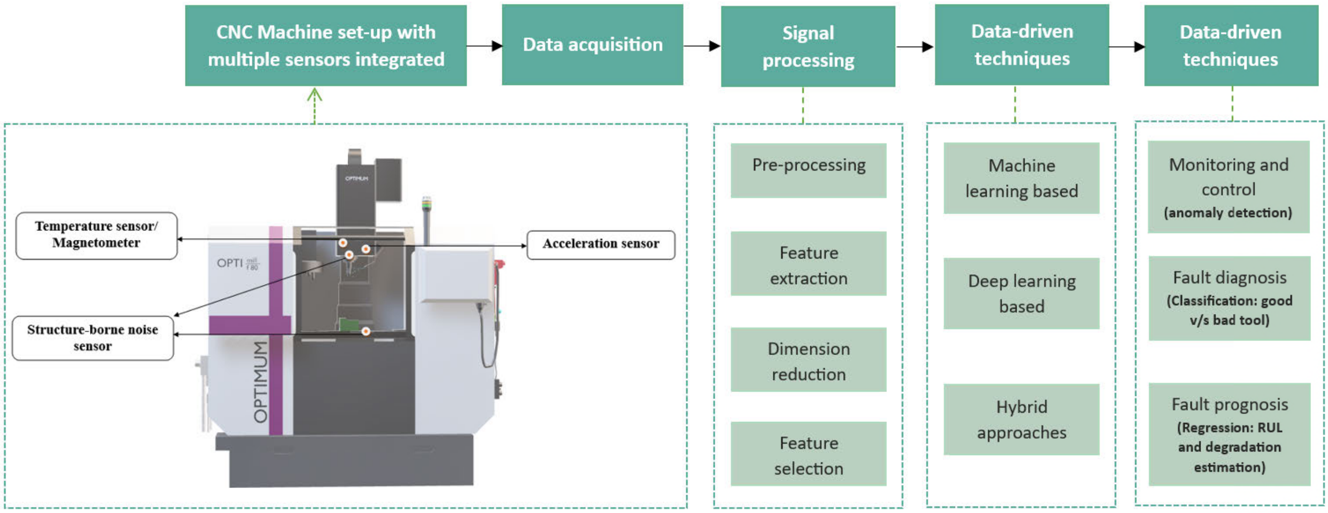

FIGURE 6. An illustration showing the global TCM systems process.

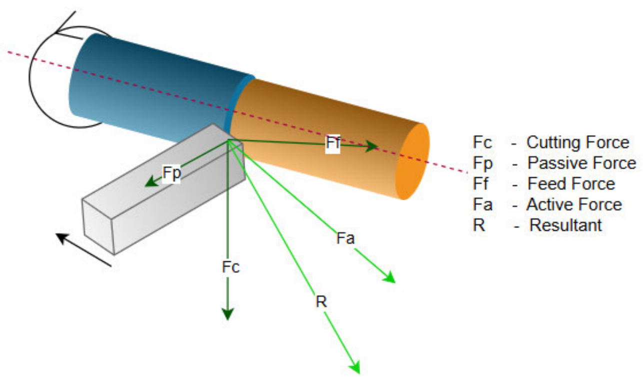

FIGURE 7. Forces acting on the workpiece.

is to integrate the force sensors into the tool holder. However, this comes at an additional cost. Figure 7 shows various types of cutting forces that are active during the TCM processes.

Table 5 reviews the kind of cutting force sensor that is being utilized for testing and sensor demands.

b: VIBRATION SIGNAL

Piezoelectric along with micro-electromechanical system (MEMS) accelerometers are used to measure the vibrations of the cutting tool to anticipate various aspects of the machined area, such as surface roughness and tool edge wear [89]. Sharp cutting tools produce small vibrations, and these vibrations get stronger as the tool gets worse. The unevenness and waviness of the machined area strongly correlate with the unwanted transitions of the cutting tool that are caused by tool vibrations [90]. Cutting-dependent and cutting-independent vibrations are two categories of vibrations produced while metal cutting.Cutting-independent vibrations include forced vibrations brought on by machine parts, such as uneven rotating parts. In contrast, cutting-dependent vibrations show the features of the cutting process, such as interrupted cutting. Processing the signal to differentiate between both is crucial. To accurately represent tool wear, it is essential to analyze the signal to discern between the two types of vibrations [91].

In comparison to other types of sensors like dynamometers and AE sensors, a vibration sensor is less expensive and easier to install. Nevertheless, the signals are often complex to filter, which increases the likelihood that they may deliver false information. Further, the cutting fluid directly affects the vibration signal, as does the transmission path from the vibration source to the vibration sensor location. Based on the type of vibration sensor used for experimentation and sensor specifications, a summary is presented in Table 6.

c: ACOUSTIC EMISSION SIGNAL

When a material undergoes irreversible processes like wear, chipping, and breaking of the cutting tool, chip formation, and thermal reaction, AE sensors are used to collect the radiation of the acoustic waves released. The acoustic emission (AE) signal is widely regarded as being among the most efficient ways to detect tool wear and breakage because its frequency bandwidth (10 kHz–1 MHz) is more significant than that of ambient noises and machine vibrations (1 Hz–10 kHz) [103], [108]. Furthermore, by tracking acoustic waves produced during unsteady crack development in the pre-failure phase, the AE signal may anticipate impending events and provide an opportunity to mitigate unanticipated and unfavorable occurrences.

Hence, applying the AE approach may serve as a warning system, especially in the event of failure, thereby potentially reducing production costs [109]. In the cutting process, AE signals are made up of both transient and continuous signals based on the source of the signal. While transient and burst AE signals are produced by various factors such as tool fracture, chip breakage, and tool engagement and

TABLE 5. Studies using cutting force as an input.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[67]	2002	Milling	C1040 Steel	Kistler 9263 Dynamometer	F_n= 0.09-0.90 m/min, F_n= 0.12 mm/rev a_p= 0.86-0.14 mm
[68]	2005	Milling	Ck45	Kistler 9123B Dynamometer	V_c = 250,300,350 m/min F_n= 0.08,0.1,0.12 mm/rev
[69]	2006	Milling	T6061 aluminium alloy	Kistler 9254 Quartz	F_n= 0.05-0.1 mm/tooth
[70]	2012	Milling	Inconel Alloy 718	Kistler 9265B Dynamometer	V_c = 8000-30000 m/min, F_n= 10-50 microm/tooth, a_p= 10.15-0.3 mm,
[71]	2012	Milling	ASSAB718HH	Kistler 9257B Dynamometer	V_c = 800 rpm, F_n= 32 mm/min, a_p= 0.5 mm,
[72]	2015	Milling	GFRP composites	Kistler Dynamometer	V_c = 110-230 m/min, F_n= 0.16-0.32 mm/rev, a_p= 2 mm,
[73]	2016	Milling	Steel	Piezoelectric Dynamometer	V_c = 200- 370 m/min, F_n= 0.2 mm/rev, a_p= 0.6 mm,
[74]	2018	Milling	Aluminium alloy	Force sensor	V_c= 1999 rpm, a_p= 1 mm,
[75]	2018	Milling	Kennametal KC710 stainless steel and cast iron	Vibration sensors, Acoustic emission (AE), motor current sensors	F_n= 0.25-0.5 a_p= 0.75-1 mm,
[76]	2019	Milling	Inconel Alloy 718	Kistler 9265B Dynamometer	V_c = 8000-30000 m/min, a_p= 0.15-0.3 mm
[77]	2019	Milling	Steel T4	Kistler 9256A Dynamometer	V_c = 18000-30000 m/min, F_n= 0.5-6 microm/tooth, a_p= 60-100 micron
[78]	2020	Milling	Tungsten carbide	Kistler 3-component dynamometer, Kistler piezo accelerometers	V_c = 10400 rpm, F_n= 1555 mm/min, $0.2mm$
[79]	2020	Milling	Steel 1018	Kistler Dynamometer	V_c = 1500-4500 rpm, F_n= 0.38-9.31 mm/sec
[80]	2021	Milling	CGI 450	Piezoelectric dynamometer Kistler 9257B	V_c = 120-520 m/min, F_n= 0.05-0.25 mm/tooth, a_p= 0.2-1.0 mm
[81]	2022	Turning	NC10 (DIN 165CrV12), 40HNM (DIN 42CrMo4)	Triaxial force sensor Kistler type 9017B	V_c = 180-280 m/min, F_n= 0.1-0.21 mm/rev, a_p= 1-2 mm
[82]	2022	Milling	-	Dynamometer, Accelerometer, AE sensor	V_c = 45.24-75.4 m/min, F_n= 0.02-0.04 mm/tooth
[83]	2023	Milling	Metallic material	Kistler 9257 Dynamometer	F_n = 5000 mm/min
[84]	2023	Milling	Titanium Alloy	Force sensors F_n= 50–300 mm/min,	V_c = Fixed, a_p= 0.5–1.0 mm
[85]	2024	Milling	-	Force sensor	-
[86]	2024	Milling	-	Accelerometer	Open-access benchmark NASA milling datasets
[87]	2024	-	AA6013 aluminium alloy	Force sensor	-
[88]	2024	CNC machining	Aluminum alloy	Cutting force measurements	-

disengagement with the workpiece, continuous signals are produced by breaking in the primary shear region and wear on the tool flank face [109]. Regarding the two recommended locations for mounting the AE sensor—on the spindle or the workpiece— various data is reported in the available research concerning the AE sensor efficacy in TCM. However, its proximity to the signal source at the cutting area and its short signal transmission path generates more reliable signals while placed on the spindle [110]. The level of precision of the AE signal may be affected by the machine condition, the reflective surfaces that exist between the cutting region and the sensor, and the signal transmission direction, even though AE sensors are comparatively cheap and simple to incorporate into the machine [110]. Based on the type of acoustic emission sensor used for experimentation and sensor specifications, Table 7 lists all the studies related to acoustic emission for TCM.

d: MOTOR CURRENT SIGNAL

Spindle motor current is the principal energy source in cutting operations and is correlated with various aspects of the cutting zone, such as the condition of the tool. Cutting forces rise as tool edge wear progresses, increasing the drawn current [120]. The inertia of the motor rotor

TABLE 6. Studies using vibration as a signal input.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[91]	2008	Milling	Mild steel	Accelerometer (3-axis)	V_c = 1200-2250 rpm, F_n= 12-36 in/min, a_p= 0.08 mm
[92]	2008	Milling	C45 steel	Kistler 8752A50 accelerometer (1-axis)	V_c = 196-310 m/min, F_n= 0.2-0.6 mm/rev, a_p= 0.5-1 mm
[93]	2009	Milling	Thermal refining 45 steel	IV9898 Piezoelectric accelerometer (1-axis)	V_c = 8.792-21.98 m/min, F_n= 20-35 mm/min, a_p= 2-5 mm
[94]	2012	Milling	SK2 steel	Kistler 8141A accelerometer (3-axis)	V_c = 50000 rpm, F_n= 10-0.08 micro/rev, a_p= 0.2 mm
[95]	2014	Milling	Titanium alloy	Piezoelectric accelerometer (1-axis)	V_c = 597 r/min, a_p= 1 mm
[96]	2016	Milling	1.1225 steel alloy	IEPE 7132A accelerometer (3-axis)	V_c = 128 m/min, F_n= 0.12 mm/insert, a_p= 0.5 mm
[97]	2017	Milling	Titanium alloy Ti6A14V	356A16 PCB accelerometer (1-axis)	V_c = 3000-12000 rpm, F_n= 0.1-0.3 mm/rev, a_p= 0.2 mm
[75]	2018	Milling	Kennametal KC710 stainless steel and cast iron	Vibration sensors, Acoustic emission (AE), motor current sensors	F_n= 0.25-0.5 mm/rev, a_p= 0.75-1 mm
[98]	2019	Milling	Steel block S235JR	BMA280 accelerometer (1-axis)	V_c = 4245 rev/min, F_n= 680 mm/min, a_p= 18 mm
[99]	2020	Milling	TC4 work-piece	Triaxial accelerometer (Type-O3PZ0110009 produced by MARPOSS)	V_c = 120 m/min, F_n= 0.075 mm/tooth, a_p= 26 mm
[100]	2021	Milling	-	Accelerometer	-
[82]	2022	Milling	-	Dynamometer, Accelerometer, AE sensor	V_c = 45.24-75.4 m/min, F_n= 0.02-0.04 mm/tooth, a_p= 2 mm
[101]	2022	Milling	-	Accelerometer	-
[102]	2023	Face milling	MS workpiece	Piezoelectric accelerometer	V_c = 1000 rpm, F_n= 2400 mm/min, a_p= 0.5 mm
[85]	2023	Milling	-	Dynamometer to measure cutting force signals, Three piezoelectric accelerometers and one AE sensor	-
[103]	2024	Milling	-	AE transducers, vibration transducers, direct current (DC), and alternating current (AC) transducers	-
[104]	2024	Milling	-	External sensors measuring vibration, sound, and power	V_c = 826 rev/min F_n= 0.5 and 0.25 mm/rev a_p= 1.5 and 0.75 mm
[105]	2025	Milling	-	Vibration sensor	-
[106]	2025	End-face milling	-	Accelerometer	-
[107]	2025	Turning	-	Vibration sensor	-

functions as a low-pass filter, restricting the bandwidth of the signal identified and the ability to pick up high-frequency changes in cutting forces. Consequently, specific details may be lost in the recorded signal when the motor frequency has a lower value than the tool-pass frequency. However, 400 Hz two-pole induction motors are used in contemporary CNC machines, enabling frequency ranges of up to 24,000 rpm [121].

The number of instances of current sensors in TCM systems discussed in peer-reviewed literature is negligible when compared with other types of sensors [122]. However, dynamic threshold methods are frequently employed to determine the tool state in commercial TCM frameworks, where this signal is the primary input. Depending on the workpiece material and the cutting conditions, the limit changes. Motor current sensors are inexpensive and straightforward to install without obstructing the cutting zone [121]. However, at high spindle speeds, the signal becomes less sensitive to fluctuations in the cutting force and is instead affected by the state of the machine and its viscous damping of the feed mechanism. Table 8 summarizes the review of motor current in the literature.

e: TEMPERATURE SIGNAL

Temperature sensors can monitor the amount of tool wear. Still, their use in real-time TCM systems is rarely seen due to high thermal inertia, low response from encased traditional thermocouples [136], and challenges associated

TABLE 7. Studies using acoustic emission for TCM.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[111]	2008	Milling	C45 steel	FAC 500- Piezoelectric AE	V_c = 110-300 m/min, F_n= 0.05-0.5 mm/rev, a_p= 1.5 mm
[112]	2010	Milling	AISI 4340 steel	PAC- AE	V_c = 122-152 m/min, F_n= 0.08 mm/rev, a_p= 2.4-3.56 mm
[113]	2014	Milling	Q235 steel	MPA201 MICROPHONE	V_c = 160 rev/min, F_n= 262 mm/min, a_p= 0.2 mm
[114]	2015	Milling	H13 steel (mould)	8125B Kistler AE	V_c = 170-230 m/min, F_n= 200-300 mm/min, a_p= 2 mm
[115]	2016	Milling	VP80 stainless steel	Piezoelectric AE	V_c = 151 m/min, F_n= 0.08 mm/tooth, a_p= 1 mm
[116]	2017	Milling	Steel (block of 3.5% Ni)	Piezoelectric AE	V_c = 190-220 m/rev, F_n= 12-15 mm/min
[117]	2018	Milling	Titanium alloy Ti6A14V	Micro 30D	V_c = 225 m/min, F_n= 300 mm/min, a_p= 0.3 mm
[118]	2018	Milling	Titanium alloy	Micro 30D	V_c = 150-350 m/min, F_n= 300 mm/min, a_p= 0.3 mm
[119]	2019	Turning	-	Directly observed	-
[82]	2022	Milling	Ti-6Al-4V	Dynamometer, Accelerometer, AE sensor	V_c = 45.24-75.4 m/min, F_n= 0.02-0.04 mm/tooth, a_p= 2 mm
[85]	2023	Milling	-	Dynamometer, piezoelectric accelerometers and AE sensor	-
[103]	2024	Milling	-	AE transducers, vibration transducers, direct current (DC), and alternating current (AC) transducers	-
[120]	2024	Milling	-	AE sensor, accelerometer, infrared thermal camera	V_c =Various cutting speeds, F_n=Fixed, a_p= Fixed
[121]	2025	Turning	Stainless Steel 316 Vibration,	AE sensor, infrared thermal camera Optical Sensor	V_c =Fixed, F_n=0.3 - 1.5 mm, a_p= 0.15 - 0.4 mm/rev

with embedding the sensor in a rotating tool near the cutting edge, such as in milling operations. An additional method for measuring the intense heat in the Ti6Al4V cutting zone is to use a thermal imaging device [136]. But this kind of approach is inappropriate in severe machining surroundings. He et al. [63] used a temperature signal obtained from a thin-film thermocouple encased into a cutter in turning operations for measuring the wear of the tool to fix the inadequate response time of the conventional thermocouple. The robustness of this information to enhance wear estimations is highlighted by high prediction levels under a range of cutting conditions. Due to the different wear mechanisms brought on by the high cyclic thermal loading, monitoring the cutting zone temperature during the milling of hard-to-cut materials is crucial [64]. Table 9 summarizes a review for the use of temperature as a signal.

f: SPINDLE ROTATIONAL SPEED SIGNAL

The leading cause of the variations in spindle speed is the repeated shocks and friction between the cutting tool and the workpiece. The spindle motor encoder has been employed in very few studies [150], [151] to measure the immediate spindle speed, but at a low resolution of below 150 Hz. It identifies chatter, including track tool wear and breakage. By integrating a gyroscope sensor into the tool holder, it is possible to achieve a higher resolution [151]. When used with the cutting torque signal, a precise real-time assessment of the cutting power can provide immediate feedback regarding the condition of the tool and the cutting process for AC systems when compared to the motor current. Table 10 summarizes literature on spindle rotational speed.

g: AUDIBLE SOUND

Since hard materials are cut at high speeds during machining operations, nearly all produce a particular kind of sound in the audible range [163]. Unlike AE, this originates from the type of mechanisms that receive in the frequency range below 20kHz. Considering that the cutting tool enters and exits the workpiece material consecutively during intermittent cutting in milling, a discontinuous sound is produced. On the other hand, based on the material's characteristics and the cutting conditions, turning results in chips of varying shapes from the constant contact between the tool and the workpiece. In addition, a fresh cutting tool works better than a worn-out one at removing metal. This makes cutting challenging, and because of the shifting cutting tool geometry, scraping begins

TABLE 8. Studies using motor current as a signal input.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[125]	2007	-	AISI 1040	Feed motor current	V_c = 376-678 m/min, F_n= 2000-6000 mm/min a_p= 0.05-0.25 mm
[126]	2012	End milling	Stainless steel	Spindle rotary encoder	-
[127]	2014	End milling	Stainless steel	3-phase current sensor Honeywell CSNP611	- -
[128]	2016	End milling	Stainless steel	Universal power cell	-
[129]	2016	End milling	Stainless steel	Spindle power	-
[130]	2017	Face milling	CTA 213	Spindle current sensor	-
[75]	2018	Milling	Kennametal KC710 stainless steel and cast iron	Vibration sensors, AE, motor current sensors	-
[131]	2020	Milling	Various metals	Spindle motor current sensor	-
[132]	2020	Milling	Cast iron or stainless steel J45	CTA 213 current sensors	V_c = 200 m/min, F_n= 0.0833 mm/tooth a_p= 0.75-1.5 mm
[133]	2022	Milling	AISI 1045 steel	Current sensors	-
[134]	2023	Milling	Carbon steel S45C	Current sensors	-
[135]	2023	Milling	Inconel 718 (HRC-52) stainless steel	Current sensors	F_n= 1555 mm/min
[136]	2024	Milling	-	Spindle Servo Signals	-
[137]	2025	Milling	Polyurethane Foam, Aluminum, Steel	Current Sensor Force, Vibration	V_c = Fixed, F_n= 100 - 500 mm/min a_p= 0.1 - 2 mm

instead of cutting. The sound produced by a malfunctioning cutting mechanism can provide information about the state of tool wear [164]. Although microphones are essentially used for sound measurement, sound signals have certain limitations. To identify the desired quality characteristic, the frequency range of sounds originating from machine tool vibration, tool wear, breakage, chip formation, and other sources must be separated precisely. This makes a sound sensor the better choice. Table 11 outlines the study for sound as the measurement signal.

h: THERMAL IMAGING

Infrared thermography has been used to monitor tool fault while performing a micro-end milling process. It was observed that speed, feed, and the depth of cut increased as cutting tool temperature increased. Similarly, heat generation results from contact between the tool and workpiece [175]. Therefore, as cutting speed increases, so does the cutting tool temperature. To monitor the temperature range, an infrared camera also measures the temperature on the opposite end of the cutting edge. The results confirm the relationship between the rise in temperature and the cutting direction, the depth of cut feed, and speed. An infrared sensor and specially designed software helped in the high-speed machining of a bronze alloy to measure the heat transferred to the workpiece. This technique improved accuracy and required fewer tests [175].

Online temperature monitoring of the tool is required during the machining process to prevent tool failure. Numerous non-contact and contact techniques are used to monitor the temperature of the workpiece and the tool [176]. Table 12 is summarized based on the kind of camera or monitoring device being used for tool supervision.

2) DIRECT APPROACHES

Direct approaches entail a process to measure the actual value of defects directly utilizing tools like lasers and optical microscopes. This can be expensive and interfere with the manufacturing process of the measures.

a: TOOL FLANK WEAR

The two primary regions of the cutting tool, the chip surface, and the side surface, are where tool wear typically arises. As a result, tool wear is typically separated into flank wear, and crater wear [186], [187]. This is displayed in Figure 8.

The ISO 3685 standard [188] is followed while evaluating tool wear. Flank wear is the kind of wear brought on by friction between the cutting tool's insert clearance angle and the part's newly formed surface at that angle. The main load factors influencing the flank wear appear to be diffusive, mechanical, and chemical [188]. Several factors cause flank wear to form on the flank face of the cutting tool. The primary causes of flank wear are elevated cutting speeds, plastic deformation brought on by excessively high cutting temperatures, and edge chipping triggered by a high load on the cutting tool. Table 13 wraps up the review of flank wear in the study.

b: SURFACE ROUGHNESS

The nominal surface is partially used in engineering applications to express the desired surface shapes.

Surface texture is comprised of periodic departures from the part's nominal surface, which can be characterized as follows:

(i) Waviness: Irregularities whose measurement ranges exceed the sampling distance for surface roughness;

TABLE 9. Studies using temperature as a signal input.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[139]	2016	Milling	Stainless steel (SUS304), carbide bar	Thermocouple	V_c = 100-500 m/min, F_n= 0.5 mm/rev, a_p= 0.5mm
[140]	2018	Face milling	-	Type-K thermocouples	-
[141]	2018	Turning	AISI 1060 steel	3-step thermal treatment: austenizing process, the quenching process, and tempering process	V_c =4-90 m/min, F_n= 0.2-2 mm/rev,
[142]	2018	Turning	Silicon carbide particulate reinforced Al 7075	Infrared thermal sensor	V_c -40 m/min, , F_n= 0.05 mm/rev, a_p= 0.2 mm
[143]	2019	Turning	Ni-based Inconel 625	Mahr Marsurf PS 10	V_c = 40-80 m/min, F_n= 0.075-0.125 mm/rev, a_p= 0.8mm
[144]	2020	Turning	AISI D2 cold work tool steel	Temperature at the cutting zone was measured using Optris PI-450 infrared sensor	V_c = 60-120 m/min, F_n= 0.09 mm/rev, a_p= 1 mm
[145]	2020	Turning	AISI 5140 steel alloy	Kistler 8692C50, Winterthur	V_c = 150-330 m/min, F_n= 0.06-0.24 mm/rev,
[146]	2021	Turning	Hardened AISI O2 tool steel bar	Thermocouple	V_c = 100 m/min
[147]	2022	Turning	Cemented carbide insert TPGN-160308 and AISI 1045 steel	Temperature sensor	V_c = 100 m/min, F_n= 0.16 mm/rev, a_p= 1.0 mm
[148]	2023	Milling	Carbon Fiber Reinforced Polymer	Mechanistic modeling	F_n= 0.05–1.0 mm/min, a_p= 0.1–0.3 mm
[149]	2023	Turning	-	Temperature sensors, accelerometers, acoustic sensors	-
[150]	2025	Turning/Milling	Titanium Alloy	Infrared thermal camera, thermocouple	V_c = Various cutting speeds F_n= 50 - 200 mm/min, a_p= 0.5 - 3 mm
[151]	2025	Milling	Titanium alloy	TiAlN and ZrAlN thin-film sensors	-

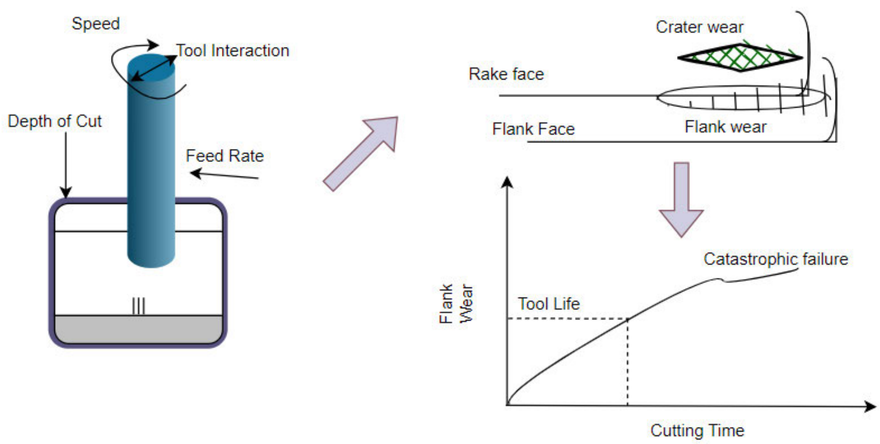

FIGURE 8. Types of tool wear.

(ii) Defects: These include fractures, scratches, stress concentration, and alignment mistakes; and

(iii) Surface roughness: The mean of the vertical deviations over a given distance on a treated surface.

Surface roughness is the average of the vertical deviations at a specific distance from a surface that has received a particular treatment. Nowadays, the average surface roughness method is widely employed to calculate surface roughness. High standards for quality are expected, particularly in sectors like the automotive and aircraft industries, where surface roughness is the only criterion to deliver this excellence [205]. Surface roughness is a significant output, particularly for machined components. In addition to shaping the part, machining is used to ensure that the correct procedure is followed to maintain surface quality. As the ultimate goal, surface roughness is a crucial process variable

TABLE 10. Studies using spindle rotational speed as a signal input.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[154]	2014	Milling	Aluminum A7075-T6 alloy	Three uniaxial accelerometers (PCB352C22)	V_c = 239.4 m/min, F_n= 0.03 mm/tooth, a_p= 25.4
[155]	2021	Milling	AL7075, AL6061	B&K4525 type accelerometer	V_c = 2700-5700 m/min, F_n= 0.5-1 mm/tooth, a_p= 1-2 mm
[156]	2021	Milling	–	Kistler 9272 dynamometer	V_c = 2000-3500 rev/min, F_n= 0.10-0.15 mm/tooth
[157]	2022	Milling	Aluminium alloy 7075-T7451	356A02 tri-axial vibration sensor, 355B03 unilateral vibration sensors	V_c = 942 m/min, F_n= 0.23 mm,
[158]	2022	Milling	Al7075 bricks	Vibration sensor (PCB tri-axial modal accelerometer)	a_p= 5 mm
[159]	2023	Milling	Steel workpiece	Two accelerometers (352A-21 from PCB)	V_c = 2000-4700 rev/min, F_n= 1200 mm/min, a_p= 0.1-0.2 mm
[160]	2023	Milling	AL7075	Kistler 9257B dynamometer	V_c = 4200-6000 rev/min, F_n= 0.05 mm/tooth, a_p= 0-4 mm
[161]	2023	Milling	Aluminum alloy Al6061	Acceleration sensor (Dytran 3263A2)	V_c = 2500-4500 rev/min, F_n= 400 mm/min, a_p= 0.1-0.4 mm
[162]	2023	Milling	TA2 titanium alloy	Acceleration sensor	V_c = 1500 rev/min, F_n= 50 - 200 mm/min, a_p= 10 mm
[163]	2024	Milling	Titanium alloy	Spindle Speed Sensor Vibration Sensor	V_c = Fixed, F_n= 60 - 180 mm/min, a_p= 0.4 - 2.5 mm
[164]	2025	Milling	Titanium Alloy	Spindle Speed Sensor, Vibration Sensor, AE sensor	V_c = Fixed, F_n= 720 mm/min, a_p= 0.5 - 3 mm

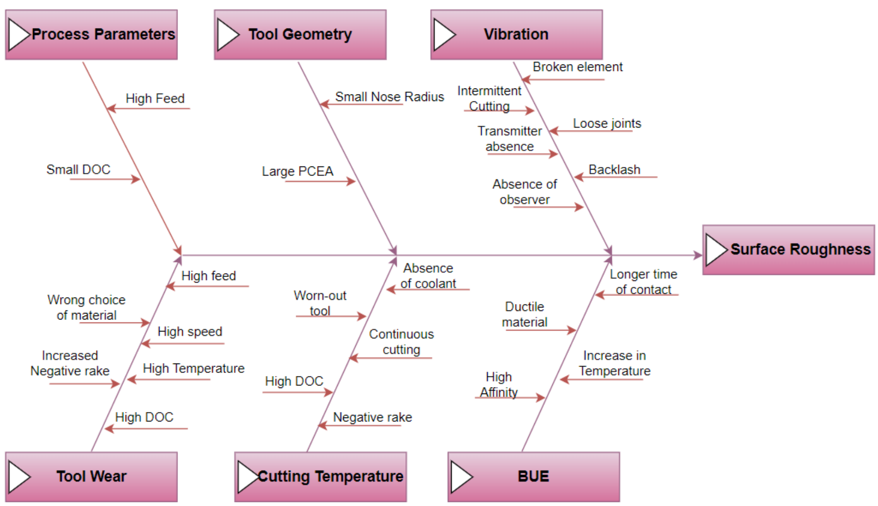

FIGURE 9. Fish-bone diagram of parameters contributing for surface roughness.

in turning. The radius of the cutting tool, the feed, and cutting speed are the variables that clearly impact the surface roughness during turning. The vibration of the machine tool impacts the surface roughness in addition to the material of the workpiece, and each of these variables is found to be statistically significant [205].

There are two primary categories into which the parameters influencing the surface roughness can be analyzed: dependent and independent variables. Feed rate, depth of cut, part material, and insert are indicated as the parameters that impact the surface roughness independently. In contrast, parameters like AE, vibration, temperature, and tool wear are dependent variables [206]. The primary objective of surface roughness investigations has been to minimize surface roughness with these parameters [206]. Figure 9 depicts different parameters that cause surface

TABLE 11. Studies using sound as a signal input.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[166]	2004	Turning	Steel alloy	Sound sensor	V_c = 80-150 m/min, F_n= 0.16-0.2 mm/rev
[167]	2012	General	-	Single microphone	-
[168]	2017	Face milling	Steel alloy 42CrMo4	Microphone (G.R.A.S. 40PH)	-
[169]	2020	Milling	#45 steel	Sound sensor Houde Automation Meter	V_c = 2300-2500 rpm, F_n= 400-500 mm/min a_p= 0.4-0.6 mm
[170]	2022	Milling	AU4G aluminum plate	Sound sensors to get vibration signals	V_c = 120-200 m/min, F_n= 0.01-0.05 mm/rev
[171]	2023	-	-	BK4189-A-021 microphone	V_c = 3000 rev/min, F_n= 250-300 mm/min, a_p= 1-1.5 mm
[172]	2023	Side milling	SiC	AE sensor	a_p= 2.5mm
[104]	2024	Milling	-	External sensors measuring vibration, sound, and power	V_c = 826 rev/min F_n= 0.5 and 0.25 mm/rev a_p= 1.5 and 0.75 mm
[173]	2024	Milling	Aluminium, steel	Sound sensors	-
[174]	2024	CNC Turning	-	Ultrasonic microphone arrays	-
[175]	2024	Milling	-	Acoustic sensors	-
[176]	2025	End-face milling	-	Vibration sensor	-

roughness. Table 14 sums up the study for surface roughness.

3) PATTERN RECOGNITION USING DIGITAL IMAGE PROCESSING

Digital image processing (DIP) with machine vision has several applications in machining operations, like surface quality control, tool wear measurement, and surface texture measurement of workpieces. Statistical data analysis, ML, signal processing, and other fields employ image processing, a pattern recognition technique which measures the textures of images. Since images contain repeating patterns, these systems only require a camera to split the image into segments for a thorough analysis [226]. Determining boundaries and segmenting an image is the main obstacle for pattern recognition algorithms. A description of each region's features is necessary for additional research and decision-making. It is necessary to distinguish between the worn and unworn regions of a cutting tool when measuring tool wear and flank wear, particularly. Table 15 displays vision-based studies.

In contrast to previously discussed sensors, image processing takes place post-machining. One drawback of this situation is that it becomes difficult to prevent excessive tool wear and breakage. However, pattern-recognition-based applications can be used when machining ceases for various reasons, like measuring surface roughness. This method can help verify the sensor data gathered and offers more details about the tool. Notably, well-designed software has a high success rate in predicting the tool's condition, significantly raising the machining quality. According to [244], 9.8% of investigations in the field of monitoring progress of turning operations for flank wear preferred DIP techniques.

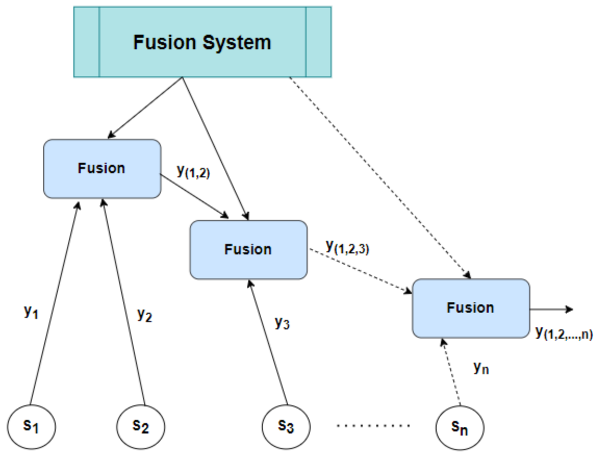

FIGURE 10. Architecture proposed by Luo and Kay.

4) MULTI-SIGNAL APPROACH

According to Luo and Kay's architecture, as per Figure 10, unprocessed sensor data is combined with nodes within an information system [245]. For instance, data $y_{(1,2)}$ can be created by combining data from sensors 1 and 2. Following that, information collected by sensor 3 will be more thoroughly fused with the resultant information $y_{(1,2)}$ in the subsequent fusion node to create data $y_{(1,2,3)}$. Similarly, the most significant fusion result comes from details $y_{(1,2,\ldots,n)}$ from the final fusion node. The authors enumerated four levels, namely, signal, pixel, feature, and symbol—that fluctuate between low and high for displaying data in various fusion processes. Multiple stages provide different degrees of information quality promotion, encompass distinct input trends in data, and are used in other systems for multiple goals.

TABLE 12. Studies demonstrating the TCM analysis using thermal based image information.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[179]	2000	Milling	P20 steel (Mold)	-	V_c =4010 rpm , F_n= 0.100 mm/tooth
[180]	2001	Milling	AISI 1045 Carbon steel	Infrared Pyrometer	V_c = 60, 600 m/min a_p= 0.025mm
[181]	2011	Milling	AI2024 T6 Aluminium alloy	Infrared thermo imaging device	F_n= 100000,160000 rpm
[182]	2012	Milling	A112 plates	Infrared camera and Infrared Pyrometer	V_c = 200-1800 m/min, F_n= 1.4 mm/rev, a_p= 3mm
[183]	2013	Milling	2A12 T4 Aluminium alloy	NI-USB-6215	V_c = 67-339.3 m/min, F_n= 8-50 micro/rev
[184]	2013	Milling	Aluminium 7050	FLIR Infrared camera	V_c = 314-628 m/min, F_n= 0.1-0.25 mm/rev, a_p= 15 mm
[177]	2015	Milling	AI6061 Aluminium alloy, AISI4340 steel	Agema Thermovision-550, and Infrared camera	V_c = 3140-6280m/min, F_n= 5-15 mm/min, a_p= 0.06-0.1mm
[185]	2021	Milling	Aluminum	Infrared thermography	V_c = Fixed, F_n= 0.2-0.5 mm/rev, a_p= 0.3-1.0 mm
[186]	2023	Turning	-	IR camera- FLIR A35 and current sensor	-
[187]	2024	Milling	#45 steel	Infrared (IR) thermal camera	V_c = 2000 rpm, F_n= 0.1 mm/rev, a_p= 0.3 mm
[188]	2024	Turning	Milling & Steel, Titanium Alloy	IoT-based thermal Sensors, Vibration Sensors	F_n= 80 - 250 mm/min, a_p= 0.3 - 1.8 mm
[150]	2025	Turning/Milling	Titanium Alloy	Infrared thermal camera, thermocouple	V_c = Various cutting speeds F_n= 50 - 200 mm/min, a_p= 0.5 - 3 mm

Raw sensor data is fed into fusion models so that it can be directly combined. The fusion models associated with this procedure fall under the signal level information fusion heading. After this fusion process, the data will have more accuracy, reduced noise, or refined features. Raw data can be fused at this level if they correspond or follow the same pattern. Signal-level fusion can sometimes be an extra step in the pre-processing of signals, or it can happen in real-time fusion scenarios. These models have also occasionally been referred to by researchers as "low-level fusion" or "raw data fusion."

A novel approach that can handle challenging real-world issues is multi-sensor information fusion. Multiple sensors work together to provide such data in industrial situations. It is simpler to assess the condition of tools and workpieces when various sensors compare data from various locations. Table 16 highlights the summary of existing works. Findings of such studies indicate that such multi-information fusion methods produce good tool wear monitoring outcomes.

B. PRE-PROCESSING

Sensor characteristics and interference from electrical, mechanical, and ambient disturbances usually require signal pre-processing, via a sensor-specific conditioner prior to or following signal digitalization. This is represented in Figure 11.

During the signal pre-processing phase, the following common signal conditioning techniques are used:

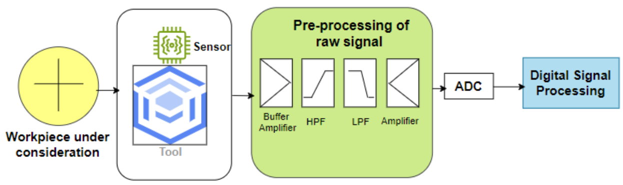

FIGURE 11. A typical overview of the pre-processing approach.

i. Amplification [260];
ii. Sampling [261];
iii. Filtering [262];
iv. Segmentation [263]; and
v. Handling missing and outlier values [264].

Table 17 highlights various pre-processing methods for TCM in SPM.

C. FEATURE EXTRACTION

A machine's condition analysis is a complicated process that frequently has an objective in mind. As a result, there are many different approaches to feature extraction, which can be divided into three main groups. Domain names include time, frequency, and time-frequency. The categorization of feature extraction appears primarily adapted based on requirements identified by the current information collection, while it has been motivated by earlier work by Riaz et al. [282].

Feature engineering, one of the most critical phases in TCM systems, is the component that makes any classification model successful. Typically, during the signal processing

TABLE 13. Studies using flank wear as a signal input.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[192]	2015	Hard Turning	AISI 4340 steel	Optical & SEM Analysis	V_c = Fixed, F_n= 50 - 150 mm/min, a_p= 0.2 - 1 mm
[193]	2016	Hard turning	AISI 4140 steel	Piezoelectric dynamometer (Kistler 9257B)	V_c = 80-150 m/min, F_n= 0.08-0.14 mm/rev, a_p= 0.1-0.3 mm
[194]	2018	Dry turning	AISI 4140 steel	Optical Microscope, Toolmakers Microscope	V_c = Fixed, F_n= 80 - 300 mm/min, a_p= 0.2 - 0.6 mm
[195]	2020	Hard turning	AISI 52100 bearing steel	Kistler 9257B dynamometer, Dino-Lite AM4113 T digital Microscope	V_c = 200 m/min, F_n= 0.1 mm/rev, a_p= 0.1 mm
[196]	2020	Turning	304 L steel	Kistler Dynamometer -9119AA2 piezoelectric dynamometer, AE sensor	V_c = 250 m/min, F_n= 0.05-1.0 mm/rev, a_p= 1.0-2.0 mm
[197]	2020	Turning	Hardened bearing steel 100Cr6	Piezoelectric sensors-vibration and dynamometer	V_c = 180m/min , F_n= 0.08 mm/rev, a_p= 0.1 mm
[198]	2021	Turning	Inconel 718	Philips X-ray diffractometer	V_c = 60-120 m/min, F_n= 0.015-0.045 mm/rev, a_p= 0.15-0.60 mm
[199]	2021	Turning	DT4E pure iron samples	X-ray stress analyzer (XSTRESS 3000)	V_c = 80-240 m/min, F_n= 0.04-0.20 mm/rev, a_p= 0.05-0.25 mm
[200]	2021	Milling	#45 steel	Triaxial accelerometer	V_c = 2000 rev/min, F_n= 764 mm/min, a_p= 2mm
[201]	2022	Turning	AISI 4140 steel	Baumer® EXG50 monochrome camera with CMOS sensor	V_c = 70-130 m/min, F_n= 0.1-0.2 mm/rev, a_p= 0.3-0.5 mm
[202]	2022	Milling	HRC52, stainless steel	Kistler quartz three-component platform dynamometer	V_c = 10,400 rev/min, F_n= 1555 mm/min, a_p= 0.001 mm
[203]	2023	Turning	16MC5 case-hardened steel	2D Taylor Hobson profilometer	V_c = 24-96 m/min, F_n= 0.050-0.256 mm/rev, a_p= 0.1-0.3 mm
[204]	2023	Turning	Stainless steel	Kistler 9257A, strain sensor, vibration, AE, microphone	V_c = 1000 rpm, F_n= 0.05 mm/rev
[205]	2023	Milling	KC710	(NASA Dataset) 2 vibration sensors, 2 current sensors, and 2 AE	V_c = 10,400 rev/min, F_n= 1555 mm/min, a_p= 0.125-0.2 mm
[205]	2023	Milling	Stainless steel, Cast iron	(PHM2010 dataset) dynamometer, accelerometer, and AE	V_c = 10,400 rev/min, F_n= 413206.5 mm/min, a_p= 0.75-1.5 mm
[206]	2023	End milling	Tungsten	Digital microscope	V_c = 40-60 m/min, F_n= 0.03 mm, a_p= 3 mm
[103]	2024	Milling	-	AE transducers, vibration transducers, direct current (DC), and alternating current (AC) transducers	-
[207]	2025	Turning	AISI 410 Steel	Force & Vibration Sensors	V_c = Fixed, F_n= 100 - 250 mm/min, a_p= 0.1 - 0.5 mm

stage, physical and statistical features that convey the characteristics of the input data are constructed, while at the dimensionality reduction stage, they are optimized. By gathering characteristic features in the time, frequency, and time-frequency domains, it is possible to express the majority of the characteristics of the monitored variables. In the past, researchers have typically employed these parameters. Various characteristic features in these domains are highlighted in Table 18.

As per the proposed taxonomy, Table 19 presents an overview categorization of the statistical time, frequency, and time-frequency domain characteristics. The methods utilized to extract features, as well as those that modify the signal to make it more suited for feature extraction, fall under the three core domains of time, frequency, and time-frequency that have been maintained in the adopted classification. Apart from the three basic domain classes, there are two further categories that cover particular situations that either barely

TABLE 14. Studies using surface roughness as a signal.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[210]	2015	Hard turning	AISI 4140 steel	Surftest SJ-201 Mitutoyo roughness tester, optical microscope (Nikon make)	V_c =100-240 rev/min, F_n= 0.05-0.15 mm/min, a_p=0.1-0.3 mm
[211]	2016	Turning	Austempered ductile iron ASTM grade 3	-	V_c = 50-150 m/min, F_n= 0.04-0.12 mm/rev, a_p= 0.2=0.4 mm
[212]	2017	Turning	AISI 1040 steel	SJ-210 surface roughness measuring device	V_c =200-275 m/min , F_n= 0.15-0.45 mm/rev, a_p= 1.5-405 mm
[213]	2019	Turning	#45 steel	VAST SD-11 instrument	V_c = 20 m/min
[214]	2020	End Milling	-	Vibration Sensor	F_n= 0.05 - 0.075 mm/tooth, a_p= 0.5-1.5mm
[215]	2020	Turning	SS410 steel	Kistler tool force dynamometer, piezoelectric type vibrometer, tool makers microscope	V_c =80=120 m/min, F_n= 0.08-0.12 mm/rev, a_p= 0.4-0.6 mm
[216]	2021	Turning	9XC Steel	Vibration sensor	F_n= 0.06 mm/rev
[217]	2021	Turning	AISI 5140	Accelerometer (Kistler 8692C50), AE (Kistler 8152B111) and current (Weidmüller WAS2 CMA 5/10A)	V_c = 150-330 mm/min, F_n= 0.06-0.24 mm/rev, a_p= 1-2 mm
[218]	2021	-	Iron-based Nickel alloy (A286)	Mitutoyo make surftest SJ – 411, Metzer-M make toolmakers microscope	V_c = 50-100 m/min, F_n= 0.15-0.35 mm/rev a_p= 0.3-0.6 mm
[219]	2021	Turning	AISI 5140	Vibration sensor, Sound sensor, Spindle Current	V_c = 150-330 mm/min, F_n= 0.1–0.25 mm/rev a_p= 0.5–1.5mm
[220]	2022	Milling	Carbide tools	Thermal camera (Testo 871), tracer-tipped tester (TIME 3200), SEM device	a_p= 1.5 mm
[221]	2022	Milling	AISI 5140 steel	Surface roughness device (Insize ISR C100) , Insize measurement microscope (ISM-PM200SB)	V_c = 75-100 m/min, F_n= 0.02-0.08 mm/rev
[222]	2022	Drilling	Titanium alloy plates	Three-component dynamometer Kistler 9257, ZEISS thermocouple	V_c = 15-65 m/min, F_n= 0.02-0.08 mm/rev
[223]	2023	Turning	AISI 1045 steel	Dynamometer Kistler 5070, thermographic camera ThermoPro-TP8, surface-tester-type Rugosurf 90-G	V_c = 80-160 m/min, F_n= 0.5-1.0 mm a_p= 0.045-0.135 mm/rev
[224]	2023	Milling	AISI 1038 carbon steel	FLIR E5-XT IR camera	V_c = 10,000 rpm, F_n= 0.045-0.135 mm/rev a_p= 0.5-1.0 mm
[225]	2023	Milling	AISI H13 tool steel	-	V_c = 200 mm/min, F_n= 0.1 mm/tooth
[226]	2024	Hard Turning	AISI 52100 Steel	Vibration sensor	-
[227]	2024	Turning	-	Vibration sensor	V_c = 60 m/min, F_n= 0.15 mm/rev, a_p= 1.2 mm
[228]	2025	Milling	-	Sensors integrated within a digital twin system	-

fit within the canonical domains or do not fit at all. Whereas unique instances include the employment of new or specially designed procedures for the object's specialty, hybrid cases involve applying methods from more than one domain.

1) DIMENSION REDUCTION AND FEATURE SELECTION

The features correlate with the machine's health condition after they are extracted into various domains. To select the features appropriately, the methods used are systematic feature dimension reduction and ranking [312]. This helps with the ranking of significant features that are related to the health condition of the machine.

Condition monitoring equipment has several different types of sensors installed. Each continually generates one or more features at various sampling rates between 10 Hz and 10–50 kHz. A vast amount of data is produced throughout the long monitoring period. However, not all of the features created are useful for analysis. Furthermore, operational and environmental aspects would also be crucial in expanding the dimensions of the features [313]. In this sense, only the most reliably significant and damage-sensitive features may be extracted by reducing the size of the features. This step is referred to as dimensionality reduction. Combining sensor arrays to extract similar information, such as various mode shapes that are gathered at each sensor node and then reduced to create a low-dimensional variety of features that only contain a handful of pattern forms, is one method of addressing the issue. A breakdown of dimensionality reduction methods is shown in Figure 12.

TABLE 15. Studies using digital image processing based analysis.

Reference Number	Year	Type of machining operation	Workpiece material used (Feed)	Type of sensor	Parameters Monitored
[230]	2006	Turning, Milling	EN24T (BS 970 Gr 817 M40T) Bar stock for turning and plate for milling	Monochrome CCD TV camera, Image Pro Plus	F_n= Constant
[231]	2007	CNC machine	AISI SAE 1045, 4140 steel bars	Pullnix PE2015 B/W camera	V_c =140-200 m/min , F_n= 0.2 mm/rev, a_p= 2mm
[232]	2016	End milling	-	3D laser scanning microscope (non-contact)	-
[233]	2017	End milling	-	Single-lens reflex camera	-
[234]	2018	End milling	-	CCD camera (non-contact)	-
[235]	2018	Turning	C45 carbon steel	CCD-FS-5612p at 684×512 resolution	V_c=140-220 m/min, F_n= 0.067 mm/rev, a_p= 0.6mm
[236]	2018	Face milling	-	Machine vision system	-
[237]	2019	Milling	Inconel 718	Daheng image industrial digital camera and digital optical microscope	V_c= 60 m/min F_n= 0.02 mm/rev, a_p= 0.3mm
[238]	2021	Turning	Steel alloy	Microscope with image analyser	V_c=250 m/min, F_n= 0.15 mm/rev, a_p= 1.5mm
[239]	2021	Micro-milling	Inconel 718	SEM images	V_c=10000 rev/min, F_n= 3 microm/tooth, a_p= 100microm
[240]	2022	Milling	H13 hardening steel	A20-M infrared imaging camera and thermocouple	-
[241]	2023	Milling	SDK-11	Infrared (IR) laser vision	V_c=100 m/min, F_n= 0.2 mm/rev, a_p= 1.0mm
[242]	2023	Drilling	SKD61 steel	Digital microscope (Dino-Lite AM4515ZT)	V_c=4000 rpm, F_n= 0.0075 mm/rev, a_p= 8.0mm
[243]	2024	Milling, turning	-	Digital camera and microscope	-
[244]	2024	CNC Machining	Steel, aluminum, titanium alloys	Consumer-grade camera	-
[245]	2024	Edge Profile Milling	Steel, Aluminum	Camera: computer vision	F_n= 200–500 mm/rev, a_p= 0.5–2.0
[246]	2025	CNC Milling	General	High-resolution camera	-

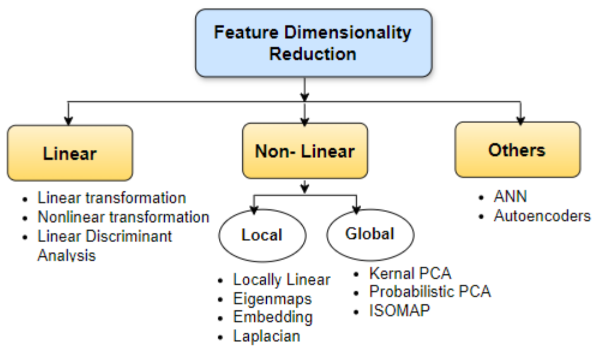

FIGURE 12. Overview of dimensionality reduction approaches (PCA: Principal component analysis).

Subset feature selection techniques are used to select the most discriminative features of the tool health state to minimize computational effort and increase the accuracy of the classification model. No relevant information can be lost during the feature selection process. Typically, conventional feature selection techniques rank the extracted features based on their sensitivity to tool conditions and then choose the top-ranked features. Feature selection techniques can be categorized as shown in Figure 13.

2) DATA-DRIVEN DECISION-MAKING METHODS

Various ML models are available to monitor and predict. These models undertake analysis of the sensor data that is utilized in data-driven models. ML algorithms based on classifiers have been widely used to support the decision-making phase, especially for monitoring the progressive tool wear [314]. Results for forecasting the tool health state look very promising for optimizing the service life of a cutting tool. This is done by preventing early replacements and limiting scraps as a result of part damage prevention [314]. Some of the more widely used ML classifiers for monitoring tool wear are artificial neural networks (ANN), Support Vector Machine (SVM), Bayesian networks, Hidden Markov model (HMM), Decision Tree (DT), k-Nearest Neighbour (kNN), Gaussian Process Regression (GPR), and fuzzy logic [315]. To thoroughly evaluate the effectiveness of SPM in TCM models, literature that concentrated on error-based, classification, prognostic, and computational metrics or a mix of these methods was investigated. Some studies employed benchmark datasets such as Prognostics Health Management (PHM) Society and NASA CMAPSS to standardize the comparisons. Priority was given to works that considered industry standards (ISO, IEEE) that guided performance

TABLE 16. Multi-signal based studies present in the literature.

Reference	Year	Type of machining	Type of sensors used	Measured data	Data processing approach	Significance
[249]	2016	General	Statistical	Process Stability	Process Control	Enhances predictive monitoring
[250]	2017	End-milling	-	Vibration, Cutting Force, Motor Current, Sound	Fuzzy logic-based	Effectively manages imprecise and uncertain data, more flexible than conventional threshold-based techniques
[251]	2019	CNC Milling	Vibration, Force, AE	Tool Wear, forces	ANN	Illustrates feasibility of ANN-based monitoring in retrofitted CNC arrangements
[252]	2019	Turning	Accelerometer, Servo motor	Vibration, Motor current	Retrofitting approach	IoT-based remote monitoring is made possible, it prolongs the life of outdated machinery
[253]	2020	Milling	Streaming sensor data and pre-calculated simulated features	Vibration, Cutting Force (active and passive)	Combining sensor and simulation data to forecast force in real time	Enhances the accuracy of force estimation in real time, it makes the process more stable
[254]	2020	Milling	-	Vibration, Cutting Force	Predicting stability by ensemble transfer learning	Adjusts to new machining conditions and materials
[255]	2021	Milling	Hall current sensor	Motor Current	Monitoring the wear status of milling tools using a stacked sparse auto-encoder	Automated extraction of hidden tool wear features
[256]	2021	Milling	-	Vibration, Cutting Force	Vibration monitoring at a single location for thin-walled milling	It is appropriate for dynamic milling processes
[257]	2021	Milling	Non-contact type microphone	Sound, Vibration	Chatter prediction using EMD	Effectively extracts dominating vibration modes
[258]	2022	Milling, Turning	AE sensor, force spindle current, temperature	Tool wear, surface quality	AI/ML based techniques	Improves wear prediction
[184]	2023	Turning	-	Vibration, Cutting Force	Turning tool TCM based on thermography	Non-contact monitoring method, recognizes wear patterns depending on temperature
[259]	2023	Milling	Vibration,	Tool wear condition cutting force, current sensors	Deep residual network	Captures high-frequency wear signals effectively
[260]	2024	Milling	Vibration, accelerometer	Tool conditions-wear, and damage	SARSA-based RL model	Facilitates decision-making effectively
[261]	2024	Turning	Piezoelectric dynamometer accelerometer	Frequency response and probe sensitivity	Filtering	Enhanced diagnostic capabilities
[262]	2025	Milling	Wireless dynamometer		Deep-learning algorithms	
[263]	2025	Milling	Vibration sensor, AE sensors	Tool Wear, surface roughness	Sensor fusion with ML framework	Enhanced tool wear prediction

evaluation to match real-world SPM requirements. Evaluation of published papers classified in the diagnostic domain enabled a taxonomy of the main classes of ML techniques utilized for this, as depicted in Figure 18.

These approaches typically use hand-crafted features as input, each with its own set of benefits and limitations. This topic has been covered in [316]. Even though ANN has been used extensively in TCM systems because it is adaptable and robust, slow convergence, the need to tune numerous biases and weights and local minima are some of its limitations [317].

Researchers have also used adaptive neuro-fuzzy inference system (ANFIS), relevance vector machine (RVM), and random forest (RF) in TCM systems for monitoring tool wear along with the normal ML methodologies. The process of selecting features is very time-consuming and requires knowledge of feature engineering. Moreover, the the sensitivity of the selected features may be reduced if the conditions based on which the model is tuned are altered. Also, these models are mostly shallow and have a very restricted ability to generalize. To raise the robustness and precision accuracy of the TCM system, it has been proposed that data-driven models be fused [318].

In addition, as the volume of the training data goes up, multi-layer neural networks and DL methods demonstrate enhanced performance as far as learning and prediction go [319]. Currently, the most widely used DL techniques like CNNs, recurrent neural networks (RNNs), long short-term memory (LSTM), and auto-encoder (AEN) are used for tracking the performance of tools [319].

In CNC machining, TCM is an essential component of SPM, where AI models evaluate tool wear, forecast failures, and maximize tool longevity. To identify wear and cracks, as well as chipping in high-resolution scans of cutting tools, CNNs are frequently utilized in image-based TCM. Real-time defect identification, quality control automation, and the reduction of manual inspection errors are all made possible by models such as ResNet, EfficientNet, and YOLO.

TABLE 17. Studies using pre-processing algorithms to remove different artifacts.

Reference	Year	Type of machining operation	Type of sensors used	Preprocessing approach
[269]	2007	Milling	Cutting force signals	Linear filtering, time-domain averaging
[270]	2010	General machining	Force, AE, vibration, optical sensors	Wavelet and ANN based approach
[271]	2015	Milling	Vibration, Cutting Force	Passband of the digital filter set to 500–700 Hz
[272]	2017	Milling	Temperature	Real time monitoring
[273]	2018	Milling	AE, force, vibration	Time, frequency analysis
[274]	2018	Drilling	Force sensor	Fuzzy-logic based approach
[275]	2018	Turning	Three orthogonal cutting forces	Integrated radial basis function based kernel principal component analysis
[276]	2020	Grinding	Sound	Segment
[277]	2020	Micro-Milling	Cutting Force	Surface response and optimization of parameters
[278]	2022	Milling	Force sensor	Signal smoothing using filtering
[279]	2022	Milling	Force sensor	Time-frequency analysis
[280]	2022	CFRP drilling	Cutting forces and power signals	First-order low pass filter with a cut-off frequency of 25Hz
[281]	2023	Drilling	Cutting forces, vibration, flow rate, pressure, spindle and feed motor currents	Handling missing and outliers, segmentation
[282]	2024	Turning and Milling	Machine Vision	Feature-based image registration
[283]	2024	Milling	Vision-Based Imaging	Local Texture Analysis Image Enhancement
[284]	2025	Milling	Force sensor	Signal smoothing using filtering
[285]	2025	End-milling	Dynamometer	Frequency analysis using Wavelet Transform

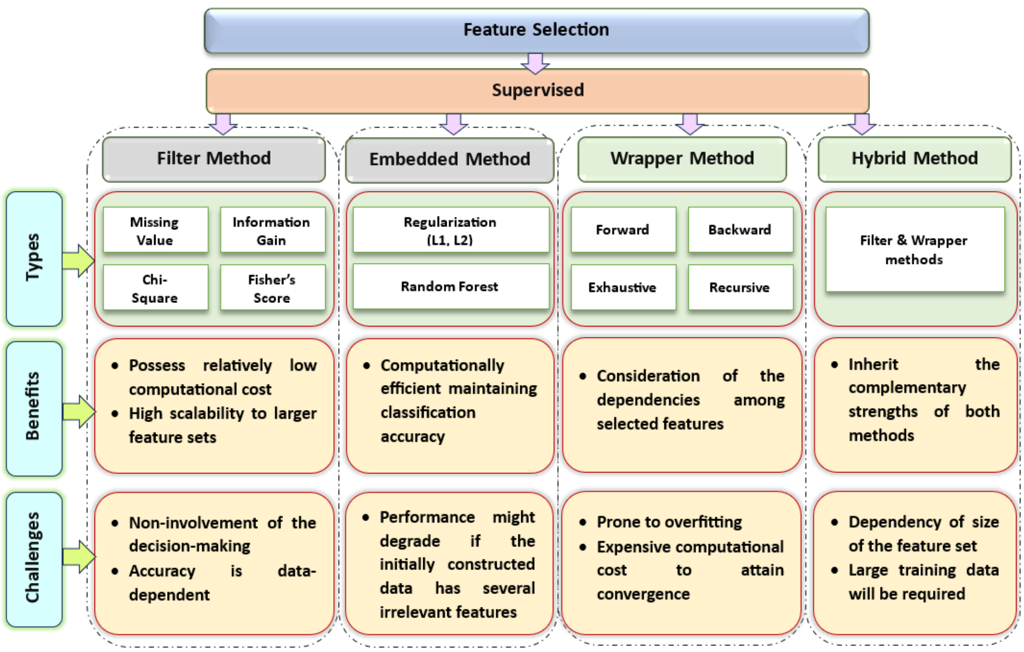

FIGURE 13. Benefits and challenges of feature selection methods.

In sensor-based TCM, time-series data from CNC sensors, including cutting forces, vibration, temperature, and AE, are processed using LSTM and gated recurrent units (GRU) to forecast the tool wear progression. Early fault identification made possible by these models permits prompt interventions before significant failures. Furthermore, to maximize tool longevity and efficiency, reinforcement learning (RL) models such as deep deterministic policy gradient and proximal policy optimization assist in dynamically adjusting machining parameters like spindle speed and feed rate depending on real-time tool conditions. By incorporating these AI frameworks, SPM in CNC machining guarantees decreased downtime, cheaper operating costs, and improved machining precision.

In the case of TCM, effective fusion of the multi-mode monitoring of data with process parameters is a crucial aspect of successful implementation. DL has a strong ability to express complex data, which is the latest evolution in the domain of AI. It can train and learn deep networks very effectively to manage the multi-level characteristic representation of data. In heterogeneous data fusion, it is uniquely superior [320]. Figure 15 depicts an end-to-end heterogeneous data fusion model that is

TABLE 18. **Frequently used features for TCM using SPM.**

Feature	Significance/ Definition
Mean	It displays the signal's core trend that is being examined
Variance	It is a metric used to measure a signal's variability as it approaches its reference mean value
Standard deviation	It displays the degree of deviation from the mean
Root Mean Square (RMS)	The root mean square value steadily declines as the defect expands
Peak	Finding and pinpointing a signal's local peaks or maxima
Peak to Peak	Determining a signal's local peaks and minima's locations and amplitudes that meet specific requirements
Skewness	In order to measure the asymmetry tendency of the vibration signal, skewness uses the probability density function (PDF)
Kurtosis	It symbolizes the considered signal's stationarity and ephemeral characteristics
Entropy	The measure of a sample's uncertainty and unpredictability is called entropy
Crest factor	The relationship between a signal's Root Mean Square and peak value. It displays a signal's extreme peaks
Form Factor	The relationship between the peak and RMS values of a signal
Clearance Factor	Peak value is expressed as a squared mean of the absolute amplitudes' square roots. The entire amount of wear that a tool can have in relation to another is known as tool clearance
Impulse Factor	Assess the relationship between a peak's height and the signal's mean level
Margin factor	It reflects the ratio of the sensor signal's peak value to its square root amplitude value
Mean frequency	It enables to provide more precise information regarding the characteristics of both localized and progressive faults in the presence of excessive noise
Root variance	It illustrates the power distribution with frequency, also referred to as the power spectrum convergence
Root Mean square frequency	It display the main frequencies' position fluctuation
Spectral Skewness	As the transitory signals blend together with the surrounding noise, it is difficult to identify the defect. By examining the frequency band and choosing a delicate frequency band that matches the bearing condition, the degree of skewness can resolve this issue
Spectral Kurtosis	It is associated with the PDF. If the function parameters are set appropriately, controlling the kurtosis should be straightforward
Lower and upper histogram boundaries	Specify the range of data distribution, aiding in the detection of truncation effects, data spread, and outliers all of which are essential for precise statistical analysis and visualization
Auto regressive moving average	Effectively forecast and process signals by capturing noise and temporal relationships
Hjorts parameters	They are frequently employed in time-series signal analysis because they can quantify signal features with little computational effort
Morphology based	Their capacity to examine and modify the structure of objects within data makes them popular in signal analysis and image processing. These methods are especially important in automated vision systems and industrial inspection, where precise analysis and decision-making depend on an awareness of forms and spatial relationships
Discrete Wavelet Transform	Allows for effective compression, noise elimination, and feature extraction by breaking down signals into their component frequencies, resulting in a multi-resolution analysis
Tunable Q-Factor Wavelet Transform	Enables customizable Q-factors and flexible time-frequency decomposition, which makes it ideal for non-stationary signal analysis
Short Time Fourier Transform	It is crucial for scenarios where frequency components fluctuate over time since it offers a precise spectral illustration for non-stationary signals
Empirical Mode Decomposition	Since EMD and its variations adaptively break down signals into Intrinsic Mode Functions, they are important for nonlinear and non-stationary signal analysis because they facilitate effective time-frequency analysis, feature extraction, and denoising

based on DL. It can design varying network structures to extract features for various monitoring signals. Moreover, it can also develop uniform representations and fusion methodologies of different data types. Table 20 summarizes suitable AI methods used across various industries for SPM in TCM.

Also, several edge devices (such as sensors or CNC machines) work together to jointly train a global model using FL, a decentralized ML technique, without exchanging raw data. The ability to jointly train models across many devices without exchanging raw data across production units is highly advantageous for TCM, especially for calculating RUL. To forecast tool wear in CNC machines while maintaining data privacy, the authors of [321] investigate FL. The FL architecture put forth by the authors allows several CNC machines to work together to train a model without exchanging raw data. LSTM networks are included in the method to record time-series dependencies during tool wear. To improve condition monitoring in ultrasonic metal welding while maintaining data privacy, the study in [322] makes use of the FL framework. The method enhances model generalization across many machines and operating environments by combining transfer learning and task personalization.

TABLE 19. Studies using time/frequency/time-frequency domain analysis.

Reference	Type of machining operation	Type of Data processed	Features extracted
[287]	Drilling	vibration	13 statistical attributes: Kurtosis, Standard Error, Maximum value, Skewness, Minimum value, Range, Count, Summation, Variance, Standard Deviation, Mode, Median, Mean
[288]	Drilling	Vibration	Standard deviation
[289]	Drilling	Vibration	Mean and variance
[290]	Milling	AE	RMS value
[291]	Milling	Forces, torque, vibration, and AE	Eighteen time domain and statistical features and 10th order predictive model
[292]	Turning	AE, vibration	Statistical and Histogram
[293]	Drilling	Vibration	RMS, standard deviation, mean, and delta
[294]	Milling	Cutting force	AV (average cutting force over each tooth period), FD (first differences of cutting forces), AC and DC component of the raw cutting force signal
[295]	Milling	Cutting force	The summation of squares of prediction error
[296]	Milling	Cutting force	Range, mean, mode, median, standard error, and kurtosis
[297]	Turning	-	Histogram and statistical features
[298]	-	AE	Auto Regressive Moving Average (ARMA) model with the Box-Jenkins approach
[299]	Turning	Vibration	ARMA
[300]	Drilling	Vibration	Kurtosis (time domain) and frequency domain analysis
[301]	Drilling	Vibration	Average harmonic wavelet coefficients and the maximum entropy spectrum peaks
[302]	End-Milling	Cutting forces	Statistical analysis
[303]	Milling	Vibration, spindle current	Bayesian inference based features
[304]	Milling	Vibration	Wavelet Packet Transform
[305]	Micro-Milling	AE sensor	Time-frequency extracted features
[306]	Milling	Vibration	Time and frequency domain analysis
[307]	Robotic Milling	Vibration, cutting force	Singularity features
[308]	Micro-Milling	AE sensor, vibration	Hidden Markov Model extracted transition probabilities
[309]	General	Vibration	VWC and MSFLA
[310]	General	Vibration	Spectral based Kurtosis
[311]	General	Vibration	Variational Mode Decomposition
[312]	General	Vibration	Variational Mode Decomposition
[313]	General	Vibration	Improved ensemble superwavelet transform
[314]	General	Vibration	Time and frequency domain analysis
[315]	General	Vibration	Entropy Weight Characteristic

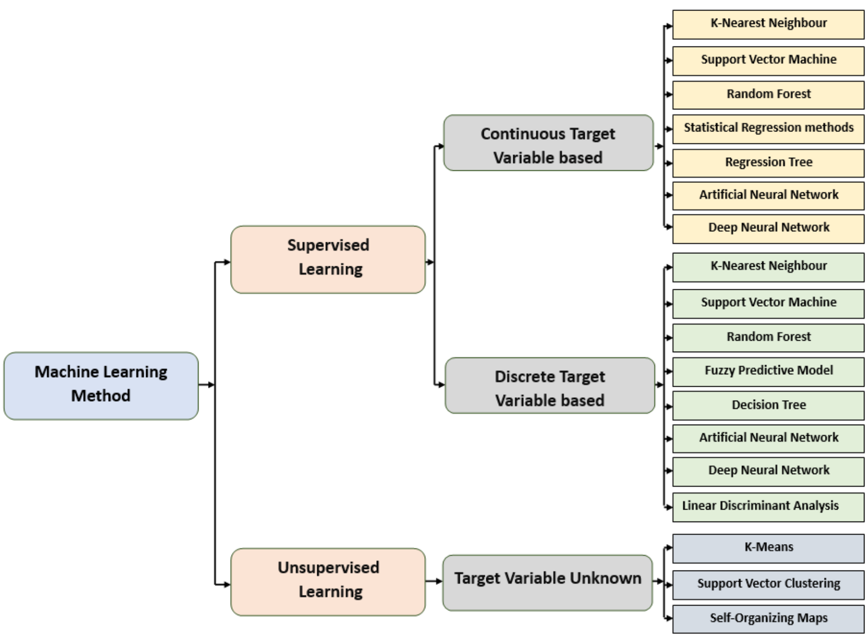

FIGURE 14. Classification of the most studied machine learning diagnostic techniques.

3) BIG DATA IN SMART TOOL CONDITION MONITORING

As a result of the evolution of modern sensing techniques along with the digitization of the CNC machining procedure, the entire machining procedure generates a large volume of heterogeneous "big data," which is made up of process parameters and signals generated during monitoring and

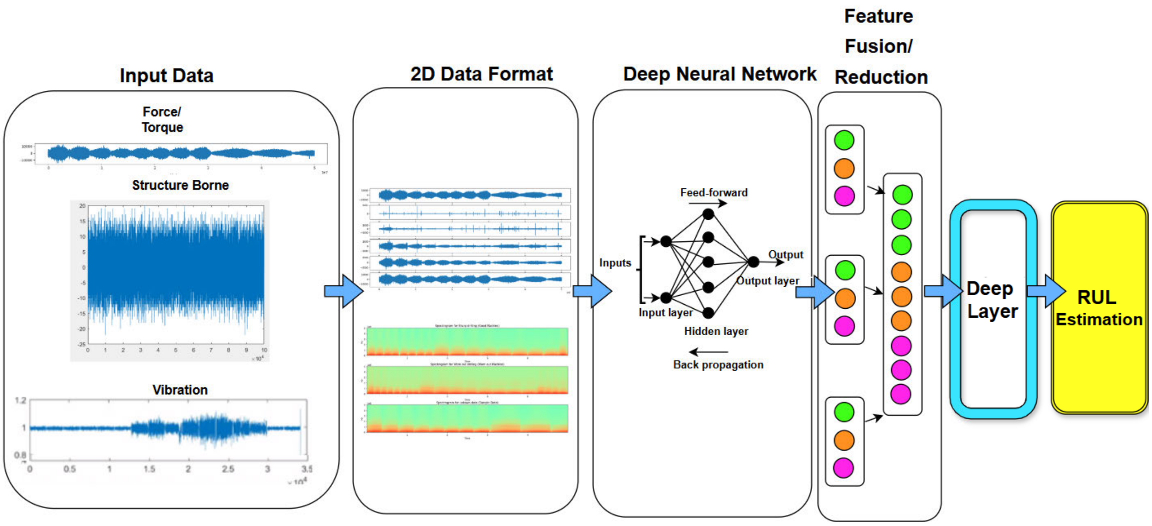

FIGURE 15. Tool wear monitoring using deep learning based diverse information fusion.

TABLE 20. Summary of suitable AI methods across various industries for SPM in TCM.

AI Methods	Suitability across industries	Requirements for industry-specific personalization	Applications		
			Automotive	Aerospace	Manufacturing
Machine learning and deep learning [327]	Indeed, widely utilized in many different sectors	Needs industry-specific training data	Vehicle health monitoring and fleet diagnostics	Forecasts avionics and engine component failures	Production lines, robotics, and CNC equipment
Digital Twin [328]	Certainly, it is utilized in manufacturing, energy, automotive, and aerospace	Examples of industry-specific models are EV drive-trains and nuclear reactors	Simulations and testing of vehicles	Monitors the structural integrity and engine performance of aircraft	Tracks the effectiveness of production,logistics and equipment
Reinforcement learning [329]	Generally used for optimization	Custom reward functions such as flight scheduling versus turbine efficiency	Enhances the lifespan of EV batteries and the effectiveness of braking systems	AI-powered adaptive maintenance schedule and flight route optimization	Boosts smart factory process efficiency
Machine vision [330]	Defect identification using images is extensively applicable	It is necessary to train AI models for industry-specific flaws such as cracks in an airplane fuselage versus body issues in a car	Recognizes manufacturing flaws in auto parts	Examines landing gear, composites, and aircraft structures	Automatically identify production line flaws

running historical records. Some big data consists of one-dimensional signals like vibration, force, acoustic emission, 3D point clouds, 2D images, and textual process data. It is because of this data that digitized and networked manufacturing is possible. It represents the idea of 4Vs: namely, volume, variety, velocity and veracity. This "big data" grows exponentially as the machining procedure progresses making it challenging to manage the acquisition of the existing data and the procedural techniques. It becomes hard to get an accurate judgment of the tool state and to optimize the procedure of machining. Currently, in depth research has been undertaken in the domain of CNC machining procedure monitoring [2]. These investigations are primarily undertaken based on the conventional theory of signal processing and AI techniques as being applied to state monitoring and diagnosing machine tools, which has partially realized the intelligent manufacturing procedure [327]. Some researchers have also attempted the STEP-compliant numerical control (STEP-NC) data methods, including advanced machining procedure data for monitoring and optimization [4]. However, while this entails a lot of post-processing, data conversion, and recognition, the expected efficiency and intelligence in machining did not materialize [3]. The primary usages of TCM are restricted and it does not include new perspectives of big data fusion for the monitoring system [327].

D. THE ROLE OF DATA VISUALIZATION

Engineers, maintenance crews, and decision-makers must properly interpret the complex outputs produced by RUL prediction models. To improve the interpretability, actionability, and reliability of these models, data visualization is essential. RUL models frequently yield unintelligible raw numerical outputs, regardless of whether they are hybrid, data-driven (ML and DL), or physics-informed.

By converting these predictions into understandable, intuitive insights, visualization improves the interpretability of RUL predictions. Furthermore, RUL forecasts generate maintenance plans, so visualization should facilitate prompt, well-informed choices. This will enhance decision-making usability. Therefore, effective data visualization fills the gap between intricate RUL models and useful insights. Organizations can increase usability, optimize maintenance procedures, and improve interpretability by utilizing time-series plots, dashboards, anomaly detection graphs, and feature importance charts.

Tableau and python dash, for instance, will assist in integrating various RUL visualizations in the context of interactive visualizations for a CNC machine using Power BI. This will make it possible to develop dashboards for monitoring in real-time. Displaying features like the RUL trend line, real-time tool wear score, and suggested maintenance window will be made easier with this information.

Actionable insights and intricate RUL models are connected using effective data visualization. Organizations can increase usability, optimize maintenance procedures, and improve interpretability by utilizing time-series visualizations, dashboards, anomaly detection illustrations, and feature-relevant infographics.

V. DISCUSSION

This data-driven-based predictive maintenance methodology for estimating the tool's useful life generates significant and crucial data about complex machining operations. Literature has shown that various sensors like dynamometers, accelerometers, current, and AE are efficacious and even preferred in data-driven condition monitoring. Although the initial implementation costs rise because of expensive sensors and data analytics, the overall advantages of reduced downtime and higher productivity are noteworthy.

A. STUDY OUTCOME

The investigation highlights the significance of data-driven SPM for estimating RUL in different CNC TCM procedures. RUL refers to the time a given machine will run before needing repairs or replacement. By assessing the RUL accurately, engineers can plan their maintenance schedules, optimize the usage of the resources provided for maintenance, and prevent delays that occur because of machine downtime. Hence, it is necessary to estimate RUL as accurately as possible in predictive maintenance plans. An in-depth literature survey reveals that using multiple sensors generates more reliable results than a single sensor approach. Multiple decision-making algorithms such as SVM, CNN, ANN and LSTM have proven to be accurate in their predictions.

SPM and TCM extensively used data-driven and physics-based methods for estimating RUL. Nevertheless, this study prioritizes data-driven approaches since they offer several useful benefits above models solely based on physics. Due to their capacity to manage intricate wear patterns, real-time forecasts, and multi-sensor data fusion, data-driven methodologies perform better in practical applications than conventional physics-based models. However, future research is still needed to develop hybrid systems that combine AI with physics-based insights.

B. DIFFICULTIES IN THE ESTIMATION OF RUL

The literature survey also revealed some of the restrictions and limitations in this domain, which are listed below:

(i) Extensive RUL estimation is required to take into account performance of the equipment from the perspective of multiple faults. Data generated by various sensors can be gathered to analyze these faults. Nevertheless, this multi-sensor data varies in size, formats, and measuring units, making it hard to analyze using a common framework of analysis. Hence, developing AI-based architectures and data analytics to use the data provided by numerous sensors effectively is a challenging task and requires further study in the future of RUL estimation;

(ii) Implementation of an intelligent RUL estimation design relies heavily on the data gathered, using different sensors. However, the working environment includes many factors, such as noise from the factory floor, temperature of the environment, and working conditions that include machining chips, flood lubrication, and so on, which have a great effect on the input signals from the sensors and can possibly result in noisy data. In turn, this noisy data impacts the accuracy of the AI-based RUL forecasts. Hence, there is a need for efficacious data pre-processing methods, outcome validation metrics, and also AI data analytics that are auto-correcting;

(iii) The development of an unbiased RUL estimation design based on AI needs a huge volume of historical data including samples from different fault events. However, such gathering of large volumes of data is not always possible in terms of cost and time. Hence, data augmentation methods to generate synthetic data are needed;

(iv) It has also come to light that it is impossible to use the same prediction algorithms for varying fault data that has been gathered under varying conditions. An amalgamation of numerous fault prediction algorithms that can be applied to various scenarios needs to be part of any given AI model;

(v) Although numerous sensors make for a high confidence level design that can make decisions, the difficulty lies in the identification of redundant and noisy signals from various sensors while undertaking data pre-processing and feature extrication;

(vi) The outcome of the estimation of RUL models based on AI has to be easy to interpret and comprehend logically so that users can figure out why a given RUL prediction was made at a given time and how the value was calculated; and

(vii) Although SPM has several advantages such as minimizing downtime and improving maintenance plans, its deployment has several challenges, mostly related to latency, computational efficiency, scalability and cost.

1) LATENCY AND COMPUTATIONAL EFFICIENCY

Lightweight models, edge computing, and improved data pretreatment help reduce latency. Model compression, GPU acceleration, and adaptive sampling enhance computational efficiency.

2) SCALABILITY AND COST

Large-scale deployment complexity: Standardization and interoperability between many systems are necessary when deploying SPM across numerous locations or a variety of equipment. IoT connectivity problems: Real-time monitoring may be hampered by network dependability problems, common in industrial settings. Heterogeneity across machines: It is challenging to develop a general predictive model that applies to all assets since different machines produce heterogeneous data. Algorithm adaptability and performance: AI models must be re-trained frequently to accommodate novel failure trends, leading to higher computational intensity.

High initial investment: Setting up SPM is costly because it calls for sophisticated sensors, cloud computing, IoT infrastructure, and AI-driven analytics; Costs of data processing and storage: The need to store, process, and analyze vast volumes of machine data in real-time raises the cost of on-premises or cloud storage; Integration with current systems: It can be expensive to retrofit SPM into older devices which calls for specialized hardware and software modifications; Skilled workforce requirement: Operating expenses are increased when staff are hired or trained for data science, AI model development, and system maintenance.

C. RECENT ADVANCEMENTS

The domain of RUL prediction making use of AI has evolved greatly in the last few years. Techniques included in this domain are shallow-structure-dependent ML methodologies to multiple hidden layer-dependent DL approaches. In the last few years, enhancements in AI have led to the strengthening of RUL estimation models. AI-based models like explainable AI, generative adversarial network (GAN), domain adaption, transfer learning, digital twin, domain adaption, and adversarial ML will go a long way towards resolving the more significant challenges currently prevailing in the RUL estimation domain in predictive maintenance. Table 21 enumerates some of these open concerns and the resolutions provided by these approaches [328], [329].

SPM within TCM has significantly been improved across a variety of industries by recent developments in sensor technologies. A thorough comparison showcasing these developments has been realized in Table 22.

In addition, industrial operations are being revolutionized by the combination of TCM with robotics, digital twins, and AI-driven SPM. A summary of important multidisciplinary techniques and their practical uses can be found below in Table 23. When TCM is combined with robotics, digital twins, and AI-powered SPM, extremely effective, self-sufficient maintenance systems are produced. Sectors including manufacturing, aerospace, and energy lead the way in the use of these technologies. In future, robotics and AI-enhanced digital twins will be essential for SPM and industrial automation.

Industry 5.0 signifies a substantial change from Industry 4.0 automation-focused approaches in SPM for TCM [330]. To monitor tool wear, forecast failures, and plan maintenance, traditional SPM mostly depended on ML algorithms and IoT sensors. Nevertheless, it frequently lacked human-machine cooperation and faced limited flexibility, opaque AI-driven choices, and data security flaws. By combining AI-driven SPM with human experience, Industry 5.0 improves decision-making and makes maintenance procedures more flexible, efficient, and intuitive [331].

A significant distinction in SPM allowed by Industry 5.0 is the real-time user-AI cooperation. AI serves as a tool for decision-making that makes recommendations in place of completely automated systems; operators can modify and disregard these recommendations in light of their own experience. This method works especially well in high-precision sectors, including aerospace and medical production, where chipping and notch wear on cutting tools can greatly affect the quality of the final product. Additionally, more localized data processing is made possible by FL, which lessens reliance on cloud computing while improving data security [332].

D. IMPLICATIONS FOR ETHICS OF AI-POWERED PREDICTIVE MAINTENANCE

Industries are transforming thanks to AI-driven SPM, which prolongs the life of machinery, maximizes productivity, and minimizes downtime. Its broad use, however, raises several ethical issues, namely regarding data privacy and employment displacement.

SPM depends on gathering a lot of data from operational systems, machine records, and IIoT sensors. However, this data frequently includes confidential company information, such as failure rates, equipment problems, and operational efficiencies. This information could, therefore, reveal trade secrets or provide rivals with an edge if it is mishandled or disclosed. A manufacturing plant's SPM system gathering real-time sensor data from CNC machines could serve as an example to demonstrate this situation. Sharing this data with outside AI suppliers may make the businessÂ production tactics more visible.

Additionally, previous maintenance records are necessary for AI models, but frequently, workers are not aware that their interactions with machines such as the ways they operate or fix equipment are being documented. When data is not properly anonymized, AI models may link it to particular workers or devices, which could lead to worker spying issues. Furthermore, constant data transmission between cloud systems, AI servers, and industrial equipment is necessary for AI-driven SPM. Hackers have the possibility of manipulating predictive models or purposefully causing

TABLE 21. Challenges and resolutions.

Difficulties in RUL predictions	Advanced AI techniques operation	Merits
Incomplete data owing to malfunctioning of the sensors	Generative Adversarial Networks (GAN)	GAN have the ability to solve class imbalance and help to retrieve missing data with synthetically generated data
Insufficient interpretability of the model corresponding to the need of RUL prediction at a certain time	Explainable AI (XAI)	Shapley Additive Explanation and Local Interpretable Model agnostic exploration techniques to decode and verify RUL estimations
Optimization of the machine maintenance schedule	Digital Twin	Improvement in the machine maintenance by using physical model based digital twin
Susceptibility of the AI/ML model to adversarial perturbations	Adversarial Machine Learning	Decrease threats related to adversarial cyber attacks on database
Insufficiency in comprehensive data containing similar distribution concerning machine prognosis	Transfer Learning	Enables smart prognosis predictions
If AI/ML model trained using a single data type, prediction strategies may be inefficient	Multi-modal data fusion	Improvement in the RUL estimation

TABLE 22. An overview of recent sensor technologies in TCM for SPM.

Sensing Technology	Overview	Merits	Uses in Industry
Wireless Smart Sensors	The sensors themselves, which include wireless communication and compute capabilities on board, enable dense deployment on huge structures	Economical, it makes installation easier and increases scalability	Monitoring the health of structures, such as bridges, manufacturing machinery
Edge Sensors with Tiny Machine Learning	Enables anomaly detection and real-time data processing by directly integrating Tiny Machine Learning models on sensors	Lowers power usage, decreases latency, and improves real-time decision-making	Mobile machinery and mining equipment
Low-Power IoT Sensors	Low-cost sensors made for safety-related uses including powerline protection and flood monitoring	Affordable, enables broad deployment, and delivers timely data	Flood surveillance and powerline security
AI-Powered Sensors	Using sensors and AI/ML algorithms, data streams are analysed to provide precise failure predictions	Increases forecast accuracy, permits preventative maintenance, and decreases downtime	Advanced manufacturing and legacy systems

errors by introducing erroneous data. Do third-party AI providers who oversee SPM have the authority to utilize customer data to enhance their models in the interim? Businesses need to ensure that AI suppliers adhere to data governance guidelines and refrain from misusing confidential data to resolve this challenge. The following may be used as data privacy mitigation strategies: i. use edge computing to process sensitive data locally rather than transferring it to the cloud; ii. train AI models across multiple machines using FL without sharing raw data; iii. create explicit data governance policies that specify ownership, usage rights, and third-party access; and iv. anonymize sensitive datasets before AI training using differential privacy techniques.

AI-powered SPM minimizes the demand for human involvement in identifying and resolving machine malfunctions. As AI automates operations that they traditionally perform, maintenance professionals and operators run the risk of losing their jobs. Further, AI-driven SPM alters the nature of employment rather than eliminating jobs. However, workers require new abilities in digital troubleshooting, data analysis, and the interpretation of AI models. Failure to adapt could result in wage reduction or unemployment. However, AI decreases the need for low-skilled maintenance personnel while increasing the need for highly trained engineers (data analysts, AI specialists).

The following are examples of mitigating techniques for job displacement: i. reskilling initiatives: teach current employees data analysis and AI-based maintenance; ii. Human-AI cooperation: AI should support human decision-making rather than completely replace it; iii. ethical AI deployment: include regulations that guarantee gradual integration instead of sudden automation; and iv. workforce diversity in AI strategy: involve staff members in AI decision-making to minimize resistance and fear.

VI. FUTURE RESEARCH WORK

In addition to the models mentioned above in each of the current advancements, the authors would like to include a few more potential approaches:

(i) A hybrid method for RUL modeling and decision-making for TCM: It was noted that numerous researchers separately work on data-driven designs or model-based techniques for calculating the RUL of the machine, which may include prediction errors due to uncertainties in the individual designs. A combination of data-driven as well as model-based architecture coupled with hybrid decision-making data analytics has the potential to decrease the occurrence of errors in RUL prediction;

(ii) Fine tuning of machine parameters: Undertaking conditioning monitoring during predictive maintenance optimizes

TABLE 23. TCM for SPM: Multidisciplinary Approaches.

Sensing Technology	Overview	Applications	Merits
Robotics with TCM	Sensors driven by AI, self-governing robots, NDT, and thermal imaging	Automotive, Energy (oil and gas), and Aerospace	Minimizes the need for human inspection, increases accuracy, and improves safety
Digital Twins with TCM	Machine learning, real-time, simulation and IoT sensors	Aviation, Energy, and Manufacturing	Increases failure prediction, maximizes asset life, and permits real-time tracking
TCM with AI and IoT	Deep Learning, Edge AI, and Big Data Analysis	Railways, Smart Grids, and Smart Buildings	Adaptive maintenance, self-learning systems, and cost savings

TABLE 24. Comprehensive analysis of cutting-edge AI methods.

Approach	Probable use cases	Feasibility	Challenges
Physics-induced DL prediction	Physics-Enhanced Milling RUL Framework: Compared to strictly data-driven models, a hybrid model that combines DL, stress-strain analysis, and thermal factors is able to forecast a milling tool's RUL with greater accuracy	Reduces reliance on extensive labelled datasets and offers interpretable RUL forecasts	It is difficult to generalize across many machining setups and requires specialized knowledge to incorporate accurate physics equations
Reinforcement learning	Self-Optimizing CNC Machining: To extend tool life, RL modifies feed rate and spindle speed throughout turning operations	Flexible enough to adjust to real-world uncertainties such as changes in tool material, adapts dynamically to ideal machining conditions	Need a significant number of training sessions, A secure training method such as a digital twin-based simulation prior to actual execution is necessary for real-world deployment
Big Data Analytics	Predictive maintenance: In drilling for instance, it is to forecast when a new bit will fail by using previous force, torque, and wear data from numerous drill bits	Managing large amounts of multi-source machining data allows for the early detection of anomalies before failure happens	Demands an enormous amount of processing power, and data labelling for controlled learning may be expensive and time-consuming
Federated learning	Aerospace Machining- Collaborative RUL prediction: A transnational RUL prediction model is trained by several aircraft part manufacturers without disclosing confidential machining data	Prevents leakage of confidential machining data and permits cross-factory cooperation without data sharing threats	Decentralized training causes slower convergence. Stable network infrastructure is necessary for federated updates

the input parameters of the equipment to enhance the RUL of the model. Researchers can consider real-time procedure parameters and degradation machine state to optimize input procedure parameters;

(iii) Holistic technique for de-noising: Very often, the signals received from the sensors are contaminated due to alterations in the working conditions of the sensors, disturbances caused by the starting of large equipment, interference from high frequency, and so on. It becomes a challenge to filter out or eradicate noise from the raw signals to make them more reliable and accurate to be able to extricate the original features. Use of integrated de-noising on the basis of energy-correlation analysis and wavelet transform packets can be made to get over de-noising of the signals sent by industrial sensors.

(iv) Sturdy Condition-Based Predictive Maintenance technique: Factors such as remote location monitoring, heterogeneous data, and network infrastructure are why condition-based predictive maintenance (CBPM) is still challenging in a complex system. The data gathered from the model is heterogeneous (discrete) in form. Some examples of such data are system error data, system state data, data gathered from the environmental sensors, data collected manually and observed by the operator's maintenance action data, etc. Smart sensors, a hybrid predictive analysis architecture, and a secure network framework can be used to implement robust CBPM for a complex system. Smart sensors can manage heterogeneous data. Hybrid predictive analysis systems can analyze the data to generate the necessary prognostic alarms, estimate the RUL of the primary components, the maintenance action needed, and the comprehensive health management of the entire model. A secure network framework can provide a framework that is flexible as well as extensible to apply CBPM successfully to complex systems;

(v) Maintenance guidelines: The goal of prescriptive maintenance methodology is to automate the maintenance procedure. Such an approach can not only monitor, predict, and come up with the requisite maintenance recommendations, but it is also able to take decisions about the necessary maintenance steps making use of advanced ML/DL as well as AI methods; and

(vi) Prognostics Health Management (PHM) as a Service: In manufacturing, cloud computing methodologies are applied by cloud manufacturing [168]. Cloud manufacturing is a manufacturing model that is heavily customer-based, and it benefits from on-demand access to a pool of dispersed and diversified equipment tools used in manufacturing to produce a single product [169]. It is possible to offer PHM as a service on the cloud, providing facilities such as PaaS, SaaS, and IaaS. The service provider can provide cloud-dependent data acquisition software and techniques that can be used for prognostic models. Leveraging the cloud infrastructure, such as storage and networking resources, a manufacturer can design a maintenance model making use of the existing platforms;

For predictive maintenance and production optimization, RUL estimate is essential in machining operations such as milling, turning, and drilling. Cutting-edge AI techniques like FL, physics-induced DL, Big Data, and RL present encouraging insights. Their practical application, viability, and possible influence are covered in Table 24.

Additionally, combining these methods can improve the accuracy and dependability of RUL predictions. For example, FL experiments and reinforcement learning training can be conducted in safe contexts using digital twins and virtual representations of manufacturing operations. At the same time, real-time federated RUL prediction may reach unprecedented efficiency levels thanks to quantum ML and neuromorphic computing.

VII. CONCLUSION

The efficiency and dependability of contemporary production systems have greatly increased using data-driven SPM in TCM. SPM systems can more accurately forecast tool wear and failures by utilizing ML, DL, and AI. This reduces unscheduled downtime and improves production schedules. Real-time analytics, feature engineering, and multi-sensor data integration have made it possible to precisely monitor tool health, enabling companies to move from reactive or preventative maintenance to completely predictive solutions. For wider deployment, issues including data heterogeneity, model generalization throughout different machining settings, and real-time implementation barriers still need to be resolved.

To improve scalability and real-time processing, future studies should concentrate on edge computing, digital twins, and hybrid AI models. Furthermore, methods such as FL will be essential for enhancing the security and interpretability of models in industrial contexts. SPM in TCM will continue to evolve due to the shift to Industry 5.0, which prioritizes sustainability, adaptive intelligence, and human-machine collaboration. SPM will keep transforming manufacturing by resolving existing constraints and incorporating cutting-edge technology, making production procedures more intelligent, robust, and economical. In order to improve generalization across tool types and lessen dependency on labeled data, self-supervised learning methods are emerging approaches in TCM employing SPM. In order to provide a precise assessment of the condition of the tool in real time, there is also increasing interest in combining multi-modal sensor data and implementing lightweight AI models at the edge.

VIII. ACRONYMS

SPM	Smart and Predicitve Maintenance
TCM	Tool condition monitoring
RUL	Remaining Useful Life
AE	Acoustic Emission
AEN	Auto-Encoder
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
ARMA	Auto-Regressive Moving Average
CBPM	Condition-Based Predictive Maintenance
CNC	Computer Numerical Control
CNN	Convolutional Neural Network
DIP	Digital Image Processing
DL	Deep Learning
DT	Decision Tree
DWT	Discrete Wavelet Transform
ERP	Enterprise Resource Planning
EV	Electric Vehicles
FL	Fedearted Learning
GAN	Generative Adversarial Networks
GPR	Gaussian Process Regression
HMM	Hidden Markov Model
IIoT	Industrial Internet of Things
IoT	Internet of Things
kNN	k-Nearest Neighbour
LSTM	Long short-term memory
MEMS	Micro-electromechanical system
MES	Manufacturing Execution System
ML	Machine Learning
PCA	Principal Component Analysis
PHM	Prognostics Health Management
RF	Random Forest
RL	Reinforcement Learning
RMS	Root Mean Square
RNN	Recurrent Neural Networks
RVM	Relevance Vector Machine
SVM	Support Vector Machine
IRR	Inter-Rater Reliability
XAI	Explainable AI

REFERENCES

[1] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, "Intelligent manufacturing in the context of industry 4.0: A review," *Engineering*, vol. 3, no. 5, pp. 616–630, Oct. 2017.
[2] C. Johnsson, "Whitepaper on smart manufacturing," Int. Org. Standardization (Smart Manufacturing Coordinating Committee, SMCC), Geneva, Switzerland, Tech. Rep. PUB 100459, 2021.
[3] *How Manufacturers Achieve Top Quartile Performance*, WC Studios, Las Vegas, NV, USA, 2018.
[4] M. Mishra, J. Martinsson, K. Goebel, and M. Rantatalo, "Bearing life prediction with informed hyperprior distribution: A Bayesian hierarchical and machine learning approach," *IEEE Access*, vol. 9, pp. 157002–157011, 2021.
[5] I.-J. Kim, C.-M. Kim, J.-H. Baek, Y.-P. Kim, Y. Lee, and Y.-C. Jang, "Structural integrity assessment of defected gas pipelines using a simplified ductile damage model," *J. Pressure Vessel Technol.*, vol. 144, no. 1, Feb. 2022, Art. no. 011302.
[6] Deloitte United States. (2025). *Optimizing Maintenance Tasks With Predictive Maintenance in Smart Factories*. [Online]. Available: https://www2.deloitte.com/us/en.html
[7] Fraunhofer Inst. for Photonic Microsystems. *Ai-based Data Evaluation for Condition Monitoring and Predictive Maintenance*. Accessed: Apr. 10, 2025. [Online]. Available: https://www.assemblymag.com
[8] Faraday Predictive. *Condition Monitoring*. Accessed: Apr. 10, 2025. [Online]. Available: https://www.faradaypredictive.com/products-and-services/condition-monitoring
[9] Weidmuller. (Mar. 2025). *Industrial Analytics: Turning Data Into Added Value*. [Online]. Available: https://www.weidmuller.com/en/solutions/solutions/industrial_analytics/index.jsp

[10] V. P. Astakhov, "Machining of hard materials-definitions and industrial applications," in *Machining of Hard Materials*. Berlin, Germany: Springer, 2011, pp. 1–32.
[11] S. Cho, S. Asfour, A. Onar, and N. Kaundinya, "Tool breakage detection using support vector machine learning in a milling process," *Int. J. Mach. Tools Manuf.*, vol. 45, no. 3, pp. 241–249, Mar. 2005.
[12] Y. Duan, H. Li, M. He, and D. Zhao, "A BiGRU autoencoder remaining useful life prediction scheme with attention mechanism and skip connection," *IEEE Sensors J.*, vol. 21, no. 9, pp. 10905–10914, May 2021.
[13] Q. Li, Z. Gao, D. Tang, and B. Li, "Remaining useful life estimation for deteriorating systems with time-varying operational conditions and condition-specific failure zones," *Chin. J. Aeronaut.*, vol. 29, no. 3, pp. 662–674, May 2016.
[14] S. Mills, "Update on ISO standards in condition monitoring and vibration," in *Proc. Int. Conf. Condition Monitor. Asset Manage.*, vol. 2023, Jan. 2023, pp. 1–11.
[15] M. El Koujok, R. Gouriveau, and N. Zerhouni, "From monitoring data to remaining useful life: An evolving approach including uncertainty," in *Proc. 34th Eur. Saf. Rel. Data Assoc., ESReDA Seminar 2nd Joint ESReDA/ESRA Seminar Supporting Technol. Adv. Maintenance Informaiton Management.*, 2008, pp. 1–12.
[16] N. Papakostas, P. Papachatzakis, V. Xanthakis, D. Mourtzis, and G. Chryssolouris, "An approach to operational aircraft maintenance planning," *Decis. Support Syst.*, vol. 48, no. 4, pp. 604–612, Mar. 2010.
[17] M. Gašperin, Đ. Juričić, P. Boškoski, and J. Vižintin, "Model-based prognostics of gear health using stochastic dynamical models," *Mech. Syst. Signal Process.*, vol. 25, no. 2, pp. 537–548, Feb. 2011.
[18] S. Sayyad, S. Kumar, A. Bongale, P. Kamat, S. Patil, and K. Kotecha, "Data-driven remaining useful life estimation for milling process: Sensors, algorithms, datasets, and future directions," *IEEE Access*, vol. 9, pp. 110255–110286, 2021.
[19] J. Rapoza. (2016). *Maintaining Virtual System Uptime in Today's Transforming It Infrastructure*. Aberdeen Group. [Online]. Available: https://www.stratus.com/assets/aberdeen-maintaining-virtual-systems-uptime.pdf
[20] D Gallichan and T Charles. (2017). *After the Fall: Cost, Causes and Consequences of Unplanned Downtime, Ge+ Servicemax*. [Online]. Available: https://www.techinnews.com/fall-costs-causes-consequences-unplanned-downtime
[21] M. Rizal, J. A. Ghani, M. Zaki Nuawi, and C. Hassan Che Haron, "A review of sensor system and application in milling process for tool condition monitoring," *Res. J. Appl. Sci., Eng. Technol.*, vol. 7, no. 10, pp. 2083–2097, Mar. 2014.
[22] M. P. Pechini, "Method of preparing lead and alkaline earth titanates and niobates and coating method using the same to form a capacitor," U.S. Patent 3 330 697, Jul. 4, 1967.
[23] B. Hoppenstedt, R. Pryss, B. Stelzer, F. Meyer-Brötz, K. Kammerer, A. Treß, and M. Reichert, "Techniques and emerging trends for state of the art equipment maintenance systems—A bibliometric analysis," *Appl. Sci.*, vol. 8, no. 6, p. 916, Jun. 2018.
[24] J. Canny, "A computational approach to edge detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vols. PAMI–8, no. 6, pp. 679–698, Nov. 1986.
[25] A. F. Allen and R. C. Brewer, "The influence of machine tool variability and tool flank wear on surface texture," in *Proc. 6th Int. MTDR Conf.*, 1965, p. 301.
[26] H. Sato, M. O-Hori, and H. Tsuwa, "Characteristics of two dimensional surface roughness—Taking self-excited chatter marks as objective," *CIRP Ann.*, vol. 30, no. 1, pp. 481–486, 1981.
[27] J. Borch, M. B. Lyne, R. E. Mark, and C. Habeger, *Handbook of Physical Testing of Paper: Volume 2*. Boca Raton, FL, USA: CRC Press, 2001.
[28] L. Liu, J. Chen, P. Fieguth, G. Zhao, R. Chellappa, and M. Pietikäinen, "From BoW to CNN: Two decades of texture representation for texture classification," *Int. J. Comput. Vis.*, vol. 127, no. 1, pp. 74–109, Jan. 2019.
[29] A. A. Kassim, M. A. Mannan, and M. Jing, "Machine tool condition monitoring using workpiece surface texture analysis," *Mach. Vis. Appl.*, vol. 11, no. 5, pp. 257–263, Feb. 2000.
[30] M. T. García-Ordás, E. Alegre-Gutiérrez, V. González-Castro, and R. Alaiz-Rodríguez, "Combining shape and contour features to improve tool wear monitoring in milling processes," *Int. J. Prod. Res.*, vol. 56, no. 11, pp. 3901–3913, Jun. 2018.
[31] B. S. Prasad and M. M. M. Sarcar, "Experimental investigation to predict the condition of cutting tool by surface texture analysis of images of machined surfaces based on amplitude parameters," *Int. J. Machining Machinability Mater.*, vol. 4, no. 2, p. 217, 2008.
[32] J. Barreiro, M. Castejón, E. Alegre, and L. K. Hernández, "Use of descriptors based on moments from digital images for tool wear monitoring," *Int. J. Mach. Tools Manuf.*, vol. 48, no. 9, pp. 1005–1013, Jul. 2008.
[33] M. H. Bharati, J. J. Liu, and J. F. MacGregor, "Image texture analysis: Methods and comparisons," *Chemometric Intell. Lab. Syst.*, vol. 72, no. 1, pp. 57–71, Jun. 2004.
[34] G. P. Stachowiak, P. Podsiadlo, and G. W. Stachowiak, "A comparison of texture feature extraction methods for machine condition monitoring and failure analysis," *Tribology Lett.*, vol. 20, no. 2, pp. 133–147, Oct. 2005.
[35] J. Zhang and T. Tan, "Brief review of invariant texture analysis methods," *Pattern Recognit.*, vol. 35, no. 3, pp. 735–747, Mar. 2002.
[36] S. Dutta, S. K. Pal, S. Mukhopadhyay, and R. Sen, "Application of digital image processing in tool condition monitoring: A review," *CIRP J. Manuf. Sci. Technol.*, vol. 6, no. 3, pp. 212–232, Jan. 2013.
[37] M. G. R. Sause, F. F. Linscheid, C. Oblinger, S. O. Gade, and S. Kalafat, "Hard-and software fusion for process monitoring during machining of fiber reinforced materials," in *Proc. Munich Symp. Lightweight Design*. Cham, Switzerland: Springer, 2021, pp. 58–62.
[38] N. Ahuja, "Dot pattern processing using Voronoi neighborhoods," *IEEE Trans. Pattern Anal. Mach. Intell.*, vols. PAMI–4, no. 3, pp. 336–343, May 1982.
[39] A. Datta, S. Dutta, S. K. Pal, and R. Sen, "Progressive cutting tool wear detection from machined surface images using Voronoi tessellation method," *J. Mater. Process. Technol.*, vol. 213, no. 12, pp. 2339–2349, Dec. 2013.
[40] S. I. Chang and J. S. Ravathur, "Computer vision based non-contact surface roughness assessment using wavelet transform and response surface methodology," *Qual. Eng.*, vol. 17, no. 3, pp. 435–451, Jul. 2005.
[41] S. Dutta, A. Datta, N. D. Chakladar, S. K. Pal, S. Mukhopadhyay, and R. Sen, "Detection of tool condition from the turned surface images using an accurate grey level co-occurrence technique," *Precis. Eng.*, vol. 36, no. 3, pp. 458–466, Jul. 2012.
[42] S. Y. Wong, J. H. Chuah, and H. J. Yap, "Technical data-driven tool condition monitoring challenges for CNC milling: A review," *Int. J. Adv. Manuf. Technol.*, vol. 107, nos. 11–12, pp. 4837–4857, Apr. 2020.
[43] I. Aldekoa, A. del Olmo, L. Sastoque-Pinilla, S. Sendino-Mouliet, U. Lopez-Novoa, and L. N. L. de Lacalle, "Early detection of tool wear in electromechanical broaching machines by monitoring main stroke servomotors," *Mech. Syst. Signal Process.*, vol. 204, Dec. 2023, Art. no. 110773.
[44] B. Siciliano, "International ifac symposium on robot control (SYROCO)," *Mechatronics*, vol. 18, no. 7, pp. 347–389, 2008.
[45] L. N. L. D. Lacalle, A. Lamikiz, J. A. Sánchez, and I. F. D. Bustos, "Recording of real cutting forces along the milling of complex parts," *Mechatronics*, vol. 16, no. 1, pp. 21–32, Feb. 2006.
[46] L. N. L. LopezdeLacalle, A. Lamikiz, J. A. Sanchez, and I. F. FernandezdeBustos, "Simultaneous measurement of forces and machine tool position for diagnostic of machining tests," *IEEE Trans. Instrum. Meas.*, vol. 54, no. 6, pp. 2329–2335, Dec. 2005.
[47] A. del Olmo, L. N. López de Lacalle, G. Martínez de Pissón, C. Pérez-Salinas, J. A. Ealo, L. Sastoque, and M. H. Fernandes, "Tool wear monitoring of high-speed broaching process with carbide tools to reduce production errors," *Mech. Syst. Signal Process.*, vol. 172, Jun. 2022, Art. no. 109003.
[48] J. Faber, M. Vistein, A. Chaloupka, M. Achzet, F. F. Linscheid, S. Kurt, and M. G. R. Sause, "Sensor-based process monitoring of in-situ polymerization in t-rtm manufacturing with caprolactam," in *Proc. SAMPE Eur. Conf.*, 2021, pp. 250–265.
[49] J. T. Roth, D. Djurdjanovic, X. Yang, L. Mears, and T. Kurfess, "Quality and inspection of machining operations: Tool condition monitoring," *J. Manuf. Sci. Eng.*, vol. 132, no. 4, Aug. 2010, Art. no. 041015.
[50] L. Dan and J. Mathew, "Tool wear and failure monitoring techniques for turning—A review," *Int. J. Mach. Tools Manuf.*, vol. 30, no. 4, pp. 579–598, Jan. 1990.
[51] J. A. Ghani, M. Rizal, M. Z. Nuawi, M. J. Ghazali, and C. H. C. Haron, "Monitoring online cutting tool wear using low-cost technique and user-friendly GUI," *Wear*, vol. 271, nos. 9–10, pp. 2619–2624, Jul. 2011.
[52] S. Dutta, S. K. Pal, and R. Sen, "Tool condition monitoring in turning by applying machine vision," *J. Manuf. Sci. Eng.*, vol. 138, no. 5, May 2016, Art. no. 051008.

[53] H. Hanachi, W. Yu, I. Y. Kim, J. Liu, and C. K. Mechefske, "Hybrid data-driven physics-based model fusion framework for tool wear prediction," *Int. J. Adv. Manuf. Technol.*, vol. 101, nos. 9–12, pp. 2861–2872, Apr. 2019.

[54] F. W. Taylor, *On the Art of Cutting Metals, Volume 23*. New York, NY, USA: American society of mechanical engineers, 1906.

[55] F. J. Amigo, G. Urbikain, O. Pereira, P. Fernández-Lucio, A. Fernández-Valdivielso, and L. N. L. de Lacalle, "Combination of high feed turning with cryogenic cooling on haynes 263 and inconel 718 superalloys," *J. Manuf. Processes*, vol. 58, pp. 208–222, Oct. 2020.

[56] J. Deutsch and D. He, "Using deep learning-based approach to predict remaining useful life of rotating components," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 1, pp. 11–20, Jan. 2018.

[57] Y. Wang, Y. Zhao, and S. Addepalli, "Remaining useful life prediction using deep learning approaches: A review," *Proc. Manuf.*, vol. 49, pp. 81–88, Jan. 2020.

[58] Z. Tao, Q. An, G. Liu, and M. Chen, "A novel method for tool condition monitoring based on long short-term memory and hidden Markov model hybrid framework in high-speed milling Ti-6Al-4 V," *Int. J. Adv. Manuf. Technol.*, vol. 105, nos. 7–8, pp. 3165–3182, Dec. 2019.

[59] J. Zhang, X. Kang, Z. Ye, L. Liu, G. Tao, and H. Cao, "Development and testing of a wireless smart toolholder with multi-sensor fusion," *Frontiers Mech. Eng.*, vol. 18, no. 4, p. 55, Dec. 2023.

[60] E. Uhlmann and T. Holznagel, "Acoustic emission-based process monitoring in the milling of carbon fibre-reinforced plastics," *CIRP J. Manuf. Sci. Technol.*, vol. 37, pp. 464–476, May 2022.

[61] T. Mohanraj and R. S. Bharath, "Real-time tool condition monitoring with the Internet of Things and machine learning algorithms," *Int. J. Comput. Integr. Manuf.*, vol. 2024, pp. 1–19, Sep. 2024.

[62] M. Plogmeyer, G. González, V. Schulze, and G. Bräuer, "Development of thin-film based sensors for temperature and tool wear monitoring during machining," *Technisches Messen*, vol. 87, no. 12, pp. 768–776, Nov. 2020.

[63] Y. Zhou and W. Xue, "Review of tool condition monitoring methods in milling processes," *Int. J. Adv. Manuf. Technol.*, vol. 96, nos. 5–8, pp. 2509–2523, May 2018.

[64] E. Salur, A. Aslan, M. Kuntoğlu, A. G.üneş, and Ö. S. Şahin, "Optimization of cutting forces during turning of composite materials," *Acad. Platf. J. Eng. Sci*, vol. 8, pp. 423–431, May 2020.

[65] C. G. Cabrera, A. C. Araujo, and D. A. Castello, "On the wavelet analysis of cutting forces for chatter identification in milling," *Adv. Manuf.*, vol. 5, no. 2, pp. 130–142, Jun. 2017.

[66] J. C. Chen and W.-L. Chen, "A tool breakage detection system using an accelerometer sensor," *J. Intell. Manuf.*, vol. 10, no. 2, pp. 187–197, Apr. 1999.

[67] M. Balazinski, E. Czogala, K. Jemielniak, and J. Leski, "Tool condition monitoring using artificial intelligence methods," *Eng. Appl. Artif. Intell.*, vol. 15, no. 1, pp. 73–80, Feb. 2002.

[68] E. Kuljanic and M. Sortino, "TWEM, a method based on cutting forces—Monitoring tool wear in face milling," *Int. J. Mach. Tools Manuf.*, vol. 45, no. 1, pp. 29–34, Jan. 2005.

[69] H. Z. Li, H. Zeng, and X. Q. Chen, "An experimental study of tool wear and cutting force variation in the end milling of inconel 718 with coated carbide inserts," *J. Mater. Process. Technol.*, vol. 180, nos. 1–3, pp. 296–304, Dec. 2006.

[70] H. Saglam and A. Unuvar, "Tool condition monitoring in milling based on cutting forces by a neural network," *Int. J. Prod. Res.*, vol. 41, no. 7, pp. 1519–1532, Jan. 2003.

[71] M. Wang and J. Wang, "CHMM for tool condition monitoring and remaining useful life prediction," *Int. J. Adv. Manuf. Technol.*, vol. 59, nos. 5–8, pp. 463–471, Mar. 2012.

[72] A. I. Azmi, "Monitoring of tool wear using measured machining forces and neuro-fuzzy modelling approaches during machining of GFRP composites," *Adv. Eng. Softw.*, vol. 82, pp. 53–64, Apr. 2015.

[73] N. H. M. Tahir, R. Muhammad, J. A. Ghani, M. Z. Nuawi, and C. H. C. Haron, "Monitoring the flank wear using piezoelectric of rotating tool of main cutting force in end milling," *Jurnal Teknologi*, vol. 78, pp. 6–10, Jun. 2016.

[74] S. Shankar, T. Mohanraj, and R. Rajasekar, "Prediction of cutting tool wear during milling process using artificial intelligence techniques," *Int. J. Comput. Integr. Manuf.*, vol. 32, no. 2, pp. 174–182, Feb. 2019.

[75] J. Wu, Y. Su, Y. Cheng, X. Shao, C. Deng, and C. Liu, "Multi-sensor information fusion for remaining useful life prediction of machining tools by adaptive network based fuzzy inference system," *Appl. Soft Comput.*, vol. 68, pp. 13–23, Jul. 2018.

[76] K. Zhu and Y. Zhang, "A generic tool wear model and its application to force modeling and wear monitoring in high speed milling," *Mech. Syst. Signal Process.*, vol. 115, pp. 147–161, Jan. 2019.

[77] W. Li and T. Liu, "Time varying and condition adaptive hidden Markov model for tool wear state estimation and remaining useful life prediction in micro-milling," *Mech. Syst. Signal Process.*, vol. 131, pp. 689–702, Sep. 2019.

[78] Z. Huang, J. Zhu, J. Lei, X. Li, and F. Tian, "Tool wear predicting based on multi-domain feature fusion by deep convolutional neural network in milling operations," *J. Intell. Manuf.*, vol. 31, no. 4, pp. 953–966, Apr. 2020.

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

[80] L. Xu, C. Huang, C. Li, J. Wang, H. Liu, and X. Wang, "Estimation of tool wear and optimization of cutting parameters based on novel ANFIS-PSO method toward intelligent machining," *J. Intell. Manuf.*, vol. 32, no. 1, pp. 77–90, Jan. 2021.

[81] S. Bombiński, J. Kossakowska, and K. Jemielniak, "Detection of accelerated tool wear in turning," *Mech. Syst. Signal Process.*, vol. 162, Jan. 2022, Art. no. 108021.

[82] J. H. N. Devia, Y. Chen, D. V. Dao, and H. Li, "Assessment of features from multiple sensors in monitoring titanium milling," *Int. J. Machining Machinability Mater.*, vol. 24, no. 1, p. 16, 2022.

[83] M. Rytir, J. Rönnecke, A. Hänel, P. Kolar, and S. Ihlenfeldt, "Influence of engagement parameters on estimation of tangential cutting force using high-frequency process data of the machine tool," *Proc. CIRP*, vol. 118, pp. 537–542, Jan. 2023.

[84] L. Wang, B. Yang, and C. Sun, "Intelligent monitoring of milling tool wear based on milling force signals and deep learning," *J. Manuf. Processes*, vol. 85, pp. 13–25, Feb. 2023.

[85] R. M. Wahul, A. M. Rahalkar, O. M. Khare, A. D. Patange, and R. N. Soman, "Making informed decisions in cutting tool maintenance in milling: A KNN-based model agnostic approach," 2023, *arXiv:2310.14629*.

[86] Y. Li, Z. Zhao, Y. Fu, and Q. Chen, "A novel approach for tool condition monitoring based on transfer learning of deep neural networks using time–frequency images," *J. Intell. Manuf.*, vol. 35, no. 3, pp. 1159–1171, Mar. 2024.

[87] N. Turšič and S. Klanč nik, "Tool condition monitoring using machine tool spindle current and long short-term memory neural network model analysis," *Sensors*, vol. 24, no. 8, p. 2490, Apr. 2024.

[88] D. Mishra, K. R. Pattipati, and G. M. Bollas, "Gaussian mixture model for tool condition monitoring," *J. Manuf. Processes*, vol. 131, pp. 1001–1013, Dec. 2024.

[89] I. Yesilyurt and H. Ozturk, "Tool condition monitoring in milling using vibration analysis," *Int. J. Prod. Res.*, vol. 45, no. 4, pp. 1013–1028, Feb. 2007.

[90] M. Kuntoğlu, A. Aslan, H. Sağlam, D. Y. Pimenov, K. Giasin, and T. Mikolajczyk, "Optimization and analysis of surface roughness, flank wear and 5 different sensorial data via tool condition monitoring system in turning of AISI 5140," *Sensors*, vol. 20, no. 16, p. 4377, Aug. 2020.

[91] J. Z. Zhang and J. C. Chen, "Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system," *Int. J. Adv. Manuf. Technol.*, vol. 39, nos. 1–2, pp. 118–128, Oct. 2008.

[92] F. J. Alonso and D. R. Salgado, "Analysis of the structure of vibration signals for tool wear detection," *Mech. Syst. Signal Process.*, vol. 22, no. 3, pp. 735–748, Apr. 2008.

[93] X. Chuangwen and C. Hualing, "Fractal analysis of vibration signals for monitoring the condition of milling tool wear," *Proc. Inst. Mech. Engineers, J, J. Eng. Tribology*, vol. 223, no. 6, pp. 909–918, Jun. 2009.

[94] W.-H. Hsieh, M.-C. Lu, and S.-J. Chiou, "Application of backpropagation neural network for spindle vibration-based tool wear monitoring in micro-milling," *Int. J. Adv. Manuf. Technol.*, vol. 61, nos. 1–4, pp. 53–61, Jul. 2012.

[95] G. F. Wang, Y. W. Yang, Y. C. Zhang, and Q. L. Xie, "Vibration sensor based tool condition monitoring using ν support vector machine and locality preserving projection," *Sens. Actuators A, Phys.*, vol. 209, pp. 24–32, Mar. 2014.
[96] C. K. Madhusudana, H. Kumar, and S. Narendranath, "Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal," *Eng. Sci. Technol., Int. J.*, vol. 19, no. 3, pp. 1543–1551, Sep. 2016.
[97] J. Liu, Y. Hu, B. Wu, and C. Jin, "A hybrid health condition monitoring method in milling operations," *Int. J. Adv. Manuf. Technol.*, vol. 92, nos. 5–8, pp. 2069–2080, Sep. 2017.
[98] 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, Jan. 2019.
[99] C. Zhou, Z. Jiang, C. Sun, and Z. Zhu, "The monitoring of milling tool tipping by estimating holder exponents of vibration," *IEEE Access*, vol. 8, pp. 96661–96668, 2020.
[100] Z. Huang, J. Zhu, J. Lei, X. Li, and F. Tian, "Tool wear monitoring with vibration signals based on short-time Fourier transform and deep convolutional neural network in milling," *Math. Problems Eng.*, vol. 2021, pp. 1–14, Jun. 2021.
[101] J. Duan, C. Hu, X. Zhan, H. Zhou, G. Liao, and T. Shi, "MS-SSPCANet: A powerful deep learning framework for tool wear prediction," *Robot. Computer-Integrated Manuf.*, vol. 78, Dec. 2022, Art. no. 102391.
[102] A. A. Jogdeo, A. D. Patange, A. M. Atnurkar, and P. R. Sonar, "Robustification of the random forest: A multitude of decision trees for fault diagnosis of face milling cutter through measurement of spindle vibrations," *J. Vib. Eng. Technol.*, vol. 12, no. 3, pp. 4521–4539, Mar. 2024.
[103] H.-T. Yau, P.-H. Kuo, and S.-W. Hong, "Milling wear prediction using an artificial neural network model," *Eng. Appl. Artif. Intell.*, vol. 135, Sep. 2024, Art. no. 108686.
[104] Y. Li, Z. Zhao, Y. Fu, and S. Cao, "Dynamic data-driven degradation method for monitoring remaining useful life of cutting tools," *Measurement*, vol. 237, Sep. 2024, Art. no. 115247.
[105] J.-D. Ryu, H.-H. Lee, K.-N. Ha, S.-R. Kim, and M. C. Lee, "Cutting force estimation using milling spindle vibration-based machine learning," *Appl. Sci.*, vol. 15, no. 5, p. 2336, Feb. 2025.
[106] M. Kodrič, J. Korbar, M. Pogač ar, and G. Čepon, "Development of a resource-efficient real-time vibration-based tool condition monitoring system using PVDF accelerometers," *Measurement*, vol. 251, Jun. 2025, Art. no. 117183.
[107] R. Liu and W. Tian, "A novel simultaneous monitoring method for surface roughness and tool wear in milling process," *Sci. Rep.*, vol. 15, no. 1, p. 8079, Mar. 2025.
[108] M. Liu, X. Yao, J. Zhang, W. Chen, X. Jing, and K. Wang, "Multi-sensor data fusion for remaining useful life prediction of machining tools by IABC-BPNN in dry milling operations," *Sensors*, vol. 20, no. 17, p. 4657, Aug. 2020.
[109] H. A. Kishawy, H. Hegab, U. Umer, and A. Mohany, "Application of acoustic emissions in machining processes: Analysis and critical review," *Int. J. Adv. Manuf. Technol.*, vol. 98, nos. 5–8, pp. 1391–1407, Sep. 2018.
[110] A. J. Vallejo and R. Morales-Menendez, "Cost-effective supervisory control system in peripheral milling using HSM," *Annu. Rev. Control*, vol. 34, no. 1, pp. 155–162, Apr. 2010.
[111] B. SICK, "On-line and indirect tool wear monitoring in turning with artificial neural networks: A review of more than a decade of research," *Mech. Syst. Signal Process.*, vol. 16, no. 4, pp. 487–546, Jul. 2002.
[112] P. Huang, J. Li, J. Sun, and J. Zhou, "Vibration analysis in milling titanium alloy based on signal processing of cutting force," *Int. J. Adv. Manuf. Technol.*, vol. 64, nos. 5–8, pp. 613–621, Feb. 2013.
[113] C. Zhou, K. Guo, and J. Sun, "An integrated wireless vibration sensing tool holder for milling tool condition monitoring with singularity analysis," *Measurement*, vol. 174, Apr. 2021, Art. no. 109038.
[114] 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.
[115] T. Li, T. Shi, Z. Tang, G. Liao, J. Duan, J. Han, and Z. He, "Real-time tool wear monitoring using thin-film thermocouple," *J. Mater. Process. Technol.*, vol. 288, Feb. 2021, Art. no. 116901.
[116] P. Krishnakumar, K. Rameshkumar, and K. I. Ramachandran, "Acoustic emission-based tool condition classification in a precision high-speed machining of titanium alloy: A machine learning approach," *Int. J. Comput. Intell. Appl.*, vol. 17, no. 3, Aug. 2018, Art. no. 1850017.
[117] M. Hassan, A. Sadek, M. H. Attia, and V. Thomson, "A novel generalized approach for real-time tool condition monitoring," *J. Manuf. Sci. Eng.*, vol. 140, no. 2, Feb. 2018, Art. no. 021010.
[118] L. Bernini, U. Malguzzi, P. Albertelli, and M. Monno, "Hybrid prognostics to estimate cutting inserts remaining useful life based on direct wear observation," *Mech. Syst. Signal Process.*, vol. 210, Mar. 2024, Art. no. 111163.
[119] Z. Gong and D. Huo, "Tool condition monitoring in micro milling of brittle materials," *Precis. Eng.*, vol. 87, pp. 11–22, May 2024.
[120] A. H. Ammouri and R. F. Hamade, "Current rise criterion: A process-independent method for tool-condition monitoring and prognostics," *Int. J. Adv. Manuf. Technol.*, vol. 72, nos. 1–4, pp. 509–519, Apr. 2014.
[121] M. Hassan, A. Sadek, and M. H. Attia, "A generalized multisensor real-time tool Condition–Monitoring approach using deep recurrent neural network," *Smart Sustain. Manuf. Syst.*, vol. 3, no. 2, pp. 41–52, Feb. 2019.
[122] M. Kuntoğlu, A. Aslan, D. Y. Pimenov, Ü. A. Usca, E. Salur, M. K. Gupta, T. Mikolajczyk, K. Giasin, W. Kapłonek, and S. Sharma, "A review of indirect tool condition monitoring systems and decision-making methods in turning: Critical analysis and trends," *Sensors*, vol. 21, no. 1, p. 108, Dec. 2020.
[123] D. R. Salgado and F. J. Alonso, "An approach based on current and sound signals for in-process tool wear monitoring," *Int. J. Mach. Tools Manuf.*, vol. 47, no. 14, pp. 2140–2152, Nov. 2007.
[124] F. Girardin, D. Rémond, and J.-F. Rigal, "A new method for detecting tool wear and breakage in milling," *Int. J. Mater. Forming*, vol. 3, no. S1, pp. 463–466, Apr. 2010.
[125] H. Liu, L. Lian, B. Li, X. Mao, S.-B. Yuan, and F. Peng, "An approach based on singular spectrum analysis and the Mahalanobis distance for tool breakage detection," *Proc. Inst. Mech. Engineers, C, J. Mech. Eng. Sci.*, vol. 228, no. 18, pp. 3505–3516, Mar. 2014.
[126] C. Drouillet, J. Karandikar, C. Nath, A.-C. Journeaux, M. E. Mansori, and T. R. Kurfess, "Tool life predictions in milling using spindle power with the neural network technique," *J. Manuf. Processes*, vol. 22, pp. 161–168, Mar. 2016.
[127] K. Harris, K. Triantafyllopoulos, E. Stillman, and T. McLeay, "A multivariate control chart for autocorrelated tool wear processes," *Qual. Rel. Eng. Int.*, vol. 32, no. 6, pp. 2093–2106, Oct. 2016.
[128] F. Aghazadeh, A. Tahan, and M. Thomas, "Tool condition monitoring using spectral subtraction and convolutional neural networks in milling process," *Int. J. Adv. Manuf. Technol.*, vol. 98, nos. 9–12, pp. 3217–3227, Oct. 2018.
[129] W. Li, J. Zhang, M. Gao, and X. Liu, "Tool condition monitoring using spindle motor current signals for milling operations," *IEEE Access*, vol. 8, pp. 88321–88332, 2020.
[130] Y. Zhou and W. Sun, "Tool wear condition monitoring in milling process based on current sensors," *IEEE Access*, vol. 8, pp. 95491–95502, 2020.
[131] Q. Zhu, B. Sun, Y. Zhou, W. Sun, and J. Xiang, "Sample augmentation for intelligent milling tool wear condition monitoring using numerical simulation and generative adversarial network," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–10, 2021.
[132] C.-H. Tai, Y.-T. Tsai, and K.-M. Li, "Establishment of real-time adaptive control strategy for milling parameters," *IEEE Access*, vol. 11, pp. 125972–125983, 2023.
[133] S. Zhang, B. Zhang, and C. Deng, "Health indicator construction for milling tool wear monitoring with multi-sensor fusion," in *Proc. CAA Symp. Fault Detection, Supervision Saf. Tech. Processes (SAFEPROCESS)*, Sep. 2023, pp. 1–5.
[134] Y. Cheng, Y. Li, G. Li, X. Liu, J. Xia, C. Liu, and X. Hao, "Tool breakage monitoring driven by the real-time predicted spindle cutting torque using spindle servo signals," *Robotics Comput.-Integrated Manufacturing*, vol. 92, 2025, Art. no. 102888. [Online]. Available: https://doi.org/10.1016/j.rcim.2024.102888.
[135] S. Nagaraj and N. Diaz-Elsayed, "Tool condition monitoring in the milling of low- to high-yield-strength materials," *Machines*, vol. 13, no. 4, p. 276, Mar. 2025.
[136] R. Teti, K. Jemielniak, G. O'Donnell, and D. Dornfeld, "Advanced monitoring of machining operations," *CIRP Ann.*, vol. 59, no. 2, pp. 717–739, 2010.
[137] H. Sasahara, K. Satake, W. Takahashi, M. Goto, and H. Yamamoto, "The effect of oil mist supply on cutting point temperature and tool wear in driven rotary cutting," *Precis. Eng.*, vol. 48, pp. 158–163, Apr. 2017.

[138] M. Rizal, J. A. Ghani, M. Z. Nuawi, and C. H. C. Haron, "An embedded multi-sensor system on the rotating dynamometer for real-time condition monitoring in milling," *Int. J. Adv. Manuf. Technol.*, vol. 95, nos. 1–4, pp. 811–823, Mar. 2018.

[139] M. Mia, P. R. Dey, M. S. Hossain, M. T. Arafat, M. Asaduzzaman, M. S. Ullah, and S. M. T. Zobaer, "Taguchi S/N based optimization of machining parameters for surface roughness, tool wear and material removal rate in hard turning under MQL cutting condition," *Measurement*, vol. 122, pp. 380–391, Jul. 2018.

[140] D. Das and A. Chapagain, "Cutting temperature and tool flank wear during turning aluminium matrix composite in air-water spray environment–a Taguchi approach," *Mater. Today, Proc.*, vol. 5, no. 9, pp. 18527–18534, 2018.

[141] Ç. V. Yıldırım, M. Sarıkaya, T. Kıvak, and Ş. Şirin, "The effect of addition of hBN nanoparticles to nanofluid-MQL on tool wear patterns, tool life, roughness and temperature in turning of ni-based inconel 625," *Tribology Int.*, vol. 134, pp. 443–456, Jun. 2019.

[142] O. Özbek and H. Saruhan, "The effect of vibration and cutting zone temperature on surface roughness and tool wear in eco-friendly MQL turning of AISI D2," *J. Mater. Res. Technol.*, vol. 9, no. 3, pp. 2762–2772, May 2020.

[143] M. Kuntoğlu, A. Aslan, D. Y. Pimenov, K. Giasin, T. Mikolajczyk, and S. Sharma, "Modeling of cutting parameters and tool geometry for multi-criteria optimization of surface roughness and vibration via response surface methodology in turning of AISI 5140 steel," *Materials*, vol. 13, no. 19, p. 4242, Sep. 2020.

[144] Z. He, T. Shi, J. Xuan, and T. Li, "Research on tool wear prediction based on temperature signals and deep learning," *Wear*, vols. 478–479, Aug. 2021, Art. no. 203902.

[145] K. Cao, J. Han, L. Xu, T. Shi, G. Liao, and Z. Liu, "Real-time tool condition monitoring method based on in situ temperature measurement and artificial neural network in turning," *Frontiers Mech. Eng.*, vol. 17, no. 1, p. 5, Mar. 2022.

[146] J. Son, C. Mungale, S. Baruah, U. Vaidya, and T. Schmitz, "Tool wear, mechanistic force modeling, and surface finish in CFRP milling," *J. Manuf. Processes*, vol. 141, pp. 1397–1415, May 2025.

[147] S. Valizadeh Sotubadi, R. Liu, and V. Neguyen, "Explainable AI for tool wear prediction in turning," 2023, *arXiv:2308.08765*.

[148] B. Martins, C. Patacas, A. Cavaleiro, P. Faia, and F. Fernandes, "Real-time temperature monitoring during titanium alloy machining with cutting tools integrating novel thin-film sensors," *Mechanical Syst. Signal Process.*, vol. 228, 2025, Art. no. 112444.

[149] B. Martins, C. Patacas, A. Cavaleiro, P. Faia, and F. Fernandes, "Real-time temperature monitoring during titanium alloy machining with cutting tools integrating novel thin-film sensors," *Mech. Syst. Signal Process.*, vol. 228, Apr. 2025, Art. no. 112444.

[150] S. S. Patil, S. S. Pardeshi, A. D. Patange, and R. Jegadeeshwaran, "Deep learning algorithms for tool condition monitoring in milling: A review," *J. Phys., Conf. Ser.*, vol. 1969, no. 1, Jul. 2021, Art. no. 012039.

[151] A. D. Patange and R. Jegadeeshwaran, "Application of Bayesian family classifiers for cutting tool inserts health monitoring on CNC milling," *Int. J. Prognostics Health Manage.*, vol. 11, no. 2, pp. 1–21, Mar. 2021.

[152] T. P. Mahesh and R. Rajesh, "Optimal selection of process parameters in CNC end milling of al 7075-T6 aluminium alloy using a Taguchi-fuzzy approach," *Proc. Mater. Sci.*, vol. 5, pp. 2493–2502, Jan. 2014.

[153] S. Wan, X. Li, Y. Yin, and J. Hong, "Milling chatter detection by multi-feature fusion and AdaBoost-SVM," *Mech. Syst. Signal Process.*, vol. 156, Jul. 2021, Art. no. 107671.

[154] D.-D. Li, W.-M. Zhang, Y.-S. Li, F. Xue, and J. Fleischer, "Chatter identification of thin-walled parts for intelligent manufacturing based on multi-signal processing," *Adv. Manuf.*, vol. 9, no. 1, pp. 22–33, Mar. 2021.

[155] W. Mou, S. Zhu, Z. Jiang, and G. Song, "Vibration signal-based chatter identification for milling of thin-walled structure," *Chin. J. Aeronaut.*, vol. 35, no. 1, pp. 204–214, Jan. 2022.

[156] X. Mei, H. Xu, P. Feng, M. Yuan, C. Xu, Y. Ma, and F. Feng, "Online chatter monitor system based on rapid detection method and wireless communication," *Int. J. Adv. Manuf. Technol.*, vol. 122, nos. 3–4, pp. 1321–1337, Sep. 2022.

[157] K. Jeong, W. Kim, N. Kim, and J. Park, "Chatter detection in milling process with feature selection based on sub-band attention convolutional neural network," *Int. J. Adv. Manuf. Technol.*, vol. 128, nos. 1–2, pp. 181–196, Sep. 2023.

[158] P. Zhang, D. Gao, D. Hong, Y. Lü, Q. Wu, S. Zan, and Z. Liao, "Improving generalisation and accuracy of on-line milling chatter detection via a novel hybrid deep convolutional neural network," *Mech. Syst. Signal Process.*, vol. 193, Mar. 2023, Art. no. 110241.

[159] Y. Lu, H. Ma, Y. Sun, Q. Song, Z. Liu, and Z. Xiong, "An interpretable anti-noise convolutional neural network for online chatter detection in thin-walled parts milling," *Mech. Syst. Signal Process.*, vol. 206, Jan. 2024, Art. no. 110885.

[160] B. Qin, Y. Wang, K. Liu, S. Jiang, and Q. Luo, "A novel online tool condition monitoring method for milling titanium alloy with consideration of tool wear law," *Mech. Syst. Signal Process.*, vol. 199, May 2023, Art. no. 110467.

[161] K. Devarajan, T. Mohanraj, P. Pradeep, G. Sakthivel, R. Jegadeeshwaran, and A. Pramanik, "Tool condition monitoring in the milling process using deep learning and reinforcement learning," *J. Sensor Actuator Netw.*, vol. 13, no. 4, p. 42, Jul. 2024.

[162] Z. Yang, L. Li, Y. Zhang, Z. Jiang, and X. Liu, "Tool wear state monitoring in titanium alloy milling based on wavelet packet and TTAO-CNN-BiLSTM-AM," *Processes*, vol. 13, no. 1, p. 13, Dec. 2024.

[163] M. G. R. Sause, F. F. Linscheid, and M. Wiehler, "An experimentally accessible probability of detection model for acoustic emission measurements," *J. Nondestruct. Eval.*, vol. 37, no. 2, pp. 1–12, Jun. 2018.

[164] N. H. Abu-Zahra and G. Yu, "Analytical model for tool wear monitoring in turning operations using ultrasound waves," *Int. J. Mach. Tools Manuf.*, vol. 40, no. 11, pp. 1619–1635, Sep. 2000.

[165] S. Sahu and B. B. Choudhury, "Optimization of surface roughness using Taguchi methodology & prediction of tool wear in hard turning tools," *Mater. Today, Proc.*, vol. 2, nos. 4–5, pp. 2615–2623, 2015.

[166] C. Sateesh Kumar and S. K. Patel, "Experimental and numerical investigations on the effect of varying AlTiN coating thickness on hard machining performance of Al_2O_3-TiCN mixed ceramic inserts," *Surf. Coatings Technol.*, vol. 309, pp. 266–281, Jan. 2017.

[167] Y. Zhou, B. Sun, W. Sun, and Z. Lei, "Tool wear condition monitoring based on a two-layer angle kernel extreme learning machine using sound sensor for milling process," *J. Intell. Manuf.*, vol. 33, no. 1, pp. 247–258, Jan. 2022.

[168] C. A. K. A. Kounta, B. Kamsu-Foguem, F. Noureddine, and F. Tangara, "Multimodal deep learning for predicting the choice of cut parameters in the milling process," *Intell. Syst. Appl.*, vol. 16, Nov. 2022, Art. no. 200112.

[169] S. Ding, S. Zhang, and C. Yang, "Machine tool fault classification diagnosis based on audio parameters," *Results Eng.*, vol. 19, Sep. 2023, Art. no. 101308.

[170] T. Jessel, C. Byrne, M. Eaton, B. Merrifield, S. Harris, and R. Pullin, "Tool condition monitoring of diamond-coated burrs with acoustic emission utilising machine learning methods," *Int. J. Adv. Manuf. Technol.*, vol. 130, nos. 3–4, pp. 1107–1124, Jan. 2024.

[171] L. Guochao, X. Shang, S. Li, F. Bofeng, Y. Lei, and Z. Honggen, "Application of audible sound signals in tool wear monitoring: A review," *Adv. Manufacturing Sci. Technol.*, vol. 5, no. 1, 2025, Art. no. 2025003.

[172] J. Steckel, A. Aerts, E. Verreycken, D. Laurijssen, and W. Daems, "Tool wear prediction in CNC turning operations using ultrasonic microphone arrays and CNNs," 2024, *arXiv:2406.08957*.

[173] M. I. Mostafiz, E. Kim, A. S. Li, E. Bertino, M. B.-G. Jun, and A. Shakouri, "Adversarial domain adaptation for metal cutting sound detection: Leveraging abundant lab data for scarce industry data," in *Proc. IEEE 22nd Int. Conf. Ind. Informat. (INDIN)*, Aug. 2024, pp. 1–8.

[174] M. D. Atkins, F. Kienhöfer, T. J. Lu, S.-M. Chang, and T. Kim, "The role of secondary flows and separation in convective heat transfer in a rotating radial vane brake disk," *J. Heat Transf.*, vol. 143, no. 8, May 2021, Art. no. 081801.

[175] S. Bagavathiappan, B. B. Lahiri, S. Suresh, J. Philip, and T. Jayakumar, "Online monitoring of cutting tool temperature during micro-end milling using infrared thermography," *Insight-Non-Destructive Test. Condition Monitor.*, vol. 57, no. 1, pp. 9–17, Jan. 2015.

[176] M. Bäker, "Finite element simulation of high-speed cutting forces," *J. Mater. Process. Technol.*, vol. 176, nos. 1–3, pp. 117–126, Apr. 2006.

[177] T. Özel and T. Altan, "Process simulation using finite element method-prediction of cutting forces, tool stresses and temperatures in high-speed flat end milling," *Int. J. Mach. Tools Manuf.*, vol. 40, no. 5, pp. 713–738, Apr. 2000.

[178] J. Lin and C.-Y. Liu, "Measurement of cutting tool temperature by an infraredpyrometer," *Meas. Sci. Technol.*, vol. 12, no. 8, p. 1243, 2001.

[179] K. Yang, Y.-C. Liang, K.-N. Zheng, Q.-S. Bai, and W.-Q. Chen, ''Tool edge radius effect on cutting temperature in micro-end-milling process,'' *Int. J. Adv. Manuf. Technol.*, vol. 52, nos. 9–12, pp. 905–912, Feb. 2011.

[180] B. Davoodi and H. Hosseinzadeh, ''A new method for heat measurement during high speed machining,'' *Measurement*, vol. 45, no. 8, pp. 2135–2140, Jun. 2012.

[181] G. Chen, C. Ren, P. Zhang, K. Cui, and Y. Li, ''Measurement and finite element simulation of micro-cutting temperatures of tool tip and workpiece,'' *Int. J. Mach. Tools Manuf.*, vol. 75, pp. 16–26, Dec. 2013.

[182] C. H. Lauro, L. C. Brandão, atilde, and S. L. M. R. Filho, ''Monitoring the temperature of the milling process using infrared camera,'' *Sci. Res. Essays*, vol. 7, no. 23, pp. 1112–1120, Jun. 2013.

[183] M. C. Gomes, L. C. Brito, M. Bacci da Silva, and M. A. Viana Duarte, ''Tool wear monitoring in micromilling using support vector machine with vibration and sound sensors,'' *Precis. Eng.*, vol. 67, pp. 137–151, Jan. 2021.

[184] R. Kou, S.-W. Lian, N. Xie, B.-E. Lu, and X.-M. Liu, ''Image-based tool condition monitoring based on convolution neural network in turning process,'' *Int. J. Adv. Manuf. Technol.*, vol. 119, nos. 5–6, pp. 3279–3291, Mar. 2022.

[185] X. Wang and J. Yan, ''Deep learning based multi-source heterogeneous information fusion framework for online monitoring of surface quality in milling process,'' *Eng. Appl. Artif. Intell.*, vol. 133, Jul. 2024, Art. no. 108043.

[186] M. A. Mannan, A. A. Kassim, and J. Ma, ''Application of image and sound analysis techniques to monitor the condition of cutting tools,'' *Pattern Recognit. Lett.*, vol. 21, no. 11, pp. 969–979, Oct. 2000.

[187] D. E. D. Snr, ''Sensor signals for tool-wear monitoring in metal cutting operations—A review of methods,'' *Int. J. Mach. Tools Manuf.*, vol. 40, no. 8, pp. 1073–1098, 2000.

[188] D. Y. Pimenov, A. T. Abbas, M. K. Gupta, I. N. Erdakov, M. S. Soliman, and M. M. El Rayes, ''Investigations of surface quality and energy consumption associated with costs and material removal rate during face milling of AISI 1045 steel,'' *Int. J. Adv. Manuf. Technol.*, vol. 107, nos. 7–8, pp. 3511–3525, Apr. 2020.

[189] S. Sahu and A. Choudhury, ''Optimization of surface roughness using Taguchi methodology & prediction of tool wear in hard turning tools,'' *Proc. Eng.*, vol. 97, pp. 241–252, Jan. 2015.

[190] H. Aouici, M. Elbah, M. A. Yallese, B. Fnides, I. Meddour, and S. Benlahmidi, ''Performance comparison of wiper and conventional ceramic inserts in hard turning of AISI 4140 steel: Analysis of machining forces and flank wear,'' *Int. J. Adv. Manuf. Technol.*, vol. 87, nos. 5–8, pp. 2221–2244, Mar. 2016.

[191] R. E. Melgar, J. R. Calixto, and J. A. Aguilar, ''Wear analysis of TiAlN and TiCN/Al_2O_3/TiN coated carbide tools in dry turning of aisi 4140 steel,'' *Coatings*, vol. 9, no. 6, p. 392, 2018.

[192] H. A. Çetindağ, A. Çiçek, and N. Uçak, ''The effects of CryoMQL conditions on tool wear and surface integrity in hard turning of AISI 52100 bearing steel,'' *J. Manuf. Processes*, vol. 56, pp. 463–473, Aug. 2020.

[193] K. Dudzik and W. Labuda, ''The possibility of applying acoustic emission and dynamometric methods for monitoring the turning process,'' *Materials*, vol. 13, no. 13, p. 2926, Jun. 2020.

[194] P. Twardowski and M. Wiciak-Pikuła, ''Prediction of tool wear using artificial neural networks during turning of hardened steel,'' *Materials*, vol. 12, no. 19, p. 3091, Sep. 2019.

[195] A. H. Elsheikh, T. Muthuramalingam, S. Shanmugan, A. M. M. Ibrahim, B. Ramesh, A. B. Khoshaim, E. B. Moustafa, B. Bedairi, H. Panchal, and R. Sathyamurthy, ''Fine-tuned artificial intelligence model using pigeon optimizer for prediction of residual stresses during turning of inconel 718,'' *J. Mater. Res. Technol.*, vol. 15, pp. 3622–3634, Nov. 2021.

[196] A. B. Khoshaim, A. H. Elsheikh, E. B. Moustafa, M. Basha, and A. O. Mosleh, ''Prediction of residual stresses in turning of pure iron using artificial intelligence-based methods,'' *J. Mater. Res. Technol.*, vol. 11, pp. 2181–2194, Mar. 2021.

[197] D. Li, D. Yuan, D. Liang, Z. Di, M. Zhang, F. Cao, M. Xin, T. Lei, and M. Jiang, ''Tool fault diagnosis based on improved multiscale network and feature fusion,'' in *Proc. IEEE Int. Conf. Prognostics Health Manage. (ICPHM)*, Jun. 2021, pp. 1–6.

[198] P. J. Bagga, M. A. Makhesana, P. P. Darji, K. M. Patel, D. Y. Pimenov, K. Giasin, and N. Khanna, ''Tool life prognostics in CNC turning of AISI 4140 steel using neural network based on computer vision,'' *Int. J. Adv. Manuf. Technol.*, vol. 123, nos. 9–10, pp. 3553–3570, Dec. 2022.

[199] Y. Li, Y. Xiang, B. Pan, and L. Shi, ''A hybrid remaining useful life prediction method for cutting tool considering the wear state,'' *Int. J. Adv. Manuf. Technol.*, vol. 121, nos. 5–6, pp. 3583–3596, Jul. 2022.

[200] A. Hamdi and S. M. Merghache, ''Application of artificial neural networks (ANN) and gray relational analysis (GRA) to modeling and optimization of the material ratio curve parameters when turning hard steel,'' *Int. J. Adv. Manuf. Technol.*, vol. 124, no. 10, pp. 3657–3670, Feb. 2023.

[201] A. Al-Azmi, A. Al-Habaibeh, and J. Abbas, ''Sensor fusion and the application of artificial intelligence to identify tool wear in turning operations,'' *Int. J. Adv. Manuf. Technol.*, vol. 126, nos. 1–2, pp. 429–442, May 2023.

[202] L. Xi, W. Wang, J. Chen, and X. Wu, ''Appending-inspired multivariate time series association fusion for tool condition monitoring,'' *J. Intell. Manuf.*, vol. 35, no. 7, pp. 3259–3272, Oct. 2024.

[203] S. Omole, H. Dogan, A. J. G. Lunt, S. Kirk, and A. Shokrani, ''Using machine learning for cutting tool condition monitoring and prediction during machining of tungsten,'' *Int. J. Comput. Integr. Manuf.*, vol. 37, no. 6, pp. 747–771, Jun. 2024.

[204] D. Kaliyannan, M. Thangamuthu, P. Pradeep, S. Gnansekaran, J. Rakkiyannan, and A. Pramanik, ''Combining sensor fusion and a machine learning framework for cutting tool condition monitoring,'' *J. Sensor Actuator Netw.*, vol. 13, no. 2, pp. 132–145, 2025.

[205] H. Y. Valera and S. N. Bhavsar, ''Experimental investigation of surface roughness and power consumption in turning operation of EN 31 alloy steel,'' *Proc. Technol.*, vol. 14, pp. 528–534, Jan. 2014.

[206] H. Akkus, ''Investigation of surface roughness values resulting from turning aisi 1040 steel with RSM and ANN,'' *BSEU J. Sci.*, vol. 7, pp. 186–197, Apr. 2020.

[207] S. R. Das, D. Dhupal, and A. Kumar, ''Study of surface roughness and flank wear in hard turning of AISI 4140 steel with coated ceramic inserts,'' *J. Mech. Sci. Technol.*, vol. 29, no. 10, pp. 4329–4340, Oct. 2015.

[208] D. Manivel and R. Gandhinathan, ''Optimization of surface roughness and tool wear in hard turning of austempered ductile iron (grade 3) using Taguchi method,'' *Measurement*, vol. 93, pp. 108–116, Nov. 2016.

[209] K. N. Çerçi and E. Hürdoğan, ''Comparative study of multiple linear regression (MLR) and artificial neural network (ANN) techniques to model a solid desiccant wheel,'' *Int. Commun. Heat Mass Transf.*, vol. 116, Jul. 2020, Art. no. 104713.

[210] D. I. Tokarev, A. A. Drozdov, L. D. Sirotenko, and E. V. Matygullina, ''Surface roughness of steel in turning with metal buildup on the tool,'' *Russian Eng. Res.*, vol. 39, no. 10, pp. 886–888, Oct. 2019.

[211] Y.-C. Lin, K.-D. Wu, W.-C. Shih, P.-K. Hsu, and J.-P. Hung, ''Prediction of surface roughness based on cutting parameters and machining vibration in end milling using regression method and artificial neural network,'' *Appl. Sci.*, vol. 10, no. 11, p. 3941, Jun. 2020.

[212] X. A. Vasanth, P. S. Paul, and A. S. Varadarajan, ''A neural network model to predict surface roughness during turning of hardened SS410 steel,'' *Int. J. Syst. Assurance Eng. Manage.*, vol. 11, no. 3, pp. 704–715, Jun. 2020.

[213] V. T. N. Uyen and N. H. Son, ''Improving accuracy of surface roughness model while turning 9XC steel using a titanium nitride-coated cutting tool with Johnson and box-cox transformation,'' *AIMS Mater. Sci.*, vol. 8, no. 1, pp. 1–17, 2021.

[214] M. Kuntoğlu and H. Sağlam, ''Investigation of signal behaviors for sensor fusion with tool condition monitoring system in turning,'' *Measurement*, vol. 173, Mar. 2021, Art. no. 108582.

[215] M. V. Ramana, G. K. M. Rao, B. Sagar, R. K. Panthangi, and B. V. R. Ravi Kumar, ''Optimization of surface roughness and tool wear in sustainable dry turning of iron based nickel A286 alloy using Taguchi's method,'' *Cleaner Eng. Technol.*, vol. 2, Jun. 2021, Art. no. 100034.

[216] P. M. Huang and C. H. Lee, ''Estimation of tool wear and surface roughness development using deep learning and sensor fusion,'' *Sensors*, vol. 21, no. 16, p. 5321, 2021.

[217] Ü. A. Usca, M. Uzun, S. Şap, M. Kuntoğlu, K. Giasin, D. Y. Pimenov, and S. Wojciechowski, ''Tool wear, surface roughness, cutting temperature and chips morphology evaluation of Al/TiN coated carbide cutting tools in milling of Cu–B–CrC based ceramic matrix composites,'' *J. Mater. Res. Technol.*, vol. 16, pp. 1243–1259, Jan. 2022.

[218] Ü. A. Usca, M. Uzun, S. Şap, K. Giasin, D. Y. Pimenov, and C. Prakash, ''Determination of machinability metrics of AISI 5140 steel for gear manufacturing using different cooling/lubrication conditions,'' *J. Mater. Res. Technol.*, vol. 21, pp. 893–904, Nov. 2022.

[219] V. Kolesnyk, J. Peterka, O. Alekseev, A. Neshta, J. Xu, B. Lysenko, M. Sahul, J. Martinovič, and J. Hrbal, ''Application of ANN for analysis of hole accuracy and drilling temperature when drilling CFRP/Ti alloy stacks,'' *Materials*, vol. 15, no. 5, p. 1940, Mar. 2022.

[220] A. T. Abbas, A. A. Al-Abduljabbar, M. M. El Rayes, F. Benyahia, I. H. Abdelgaliel, and A. Elkaseer, "Multi-objective optimization of performance indicators in turning of AISI 1045 under dry cutting conditions," *Metals*, vol. 13, no. 1, p. 96, Jan. 2023.

[221] M. Soori and B. Arezoo, "Effect of cutting parameters on tool life and cutting temperature in milling of AISI 1038 carbon steel," *J. New Technol. Mater.*, vol. 2023, pp. 1–17, May 2023.

[222] C. Cooper, J. Zhang, Y. B. Guo, and R. X. Gao, "Surface roughness prediction through GAN-synthesized power signal as a process signature," *J. Manuf. Syst.*, vol. 68, pp. 660–669, Jun. 2023.

[223] K. V. Rao, "Assessment of tool condition and surface quality using hybrid deep neural network: CNN-LSTM-Based segmentation and statistical analysis," *J. Tribology*, vol. 147, no. 8, Aug. 2025, Art. no. 084201.

[224] C. Li, G. Zhao, D. Ji, G. Zhang, L. Liu, F. Zeng, and Z. Zhao, "Influence of tool wear and workpiece diameter on surface quality and prediction of surface roughness in turning," *Metals*, vol. 14, no. 11, p. 1205, Oct. 2024.

[225] X. Zi, S. Gao, and Y. Xie, "An online monitoring method of milling cutter wear condition driven by digital twin," *Sci. Rep.*, vol. 14, no. 1, p. 5374, Feb. 2024.

[226] T. Segreto, A. Simeone, and R. Teti, "Principal component analysis for feature extraction and NN pattern recognition in sensor monitoring of chip form during turning," *CIRP J. Manuf. Sci. Technol.*, vol. 7, no. 3, pp. 202–209, 2014.

[227] D. Kerr, J. Pengilley, and R. Garwood, "Assessment and visualisation of machine tool wear using computer vision," *Int. J. Adv. Manuf. Technol.*, vol. 28, nos. 7–8, pp. 781–791, Apr. 2006.

[228] M. Castejón-Limas, E. Alegre, J. Barreiro, and L. K. Hernández, "On-line tool wear monitoring using geometric descriptors from digital images," *Int. J. Mach. Tools Manuf.*, vol. 47, nos. 12–13, pp. 1847–1853, Apr. 2007.

[229] S. N. B. Oliaei and Y. Karpat, "Influence of tool wear on machining forces and tool deflections during micro milling," *Int. J. Adv. Manuf. Technol.*, vol. 84, nos. 9–12, pp. 1963–1980, Sep. 2015.

[230] W. Sun, B. Chen, B. Yao, X. Cao, and W. Feng, "Complex wavelet enhanced shape from shading transform for estimating surface roughness of milled mechanical components," *J. Mech. Sci. Technol.*, vol. 31, no. 2, pp. 823–833, Feb. 2017.

[231] P. Krishnakumar, K. Rameshkumar, and K. I. Ramachandran, "Machine learning based tool condition classification using acoustic emission and vibration data in high speed milling process using wavelet features," *Intell. Decis. Technol.*, vol. 12, no. 2, pp. 265–282, Mar. 2018.

[232] T. Mikołajczyk, K. Nowicki, A. Bustillo, and D. Y. Pimenov, "Predicting tool life in turning operations using neural networks and image processing," *Mech. Syst. Signal Process.*, vol. 104, pp. 503–513, May 2018.

[233] A. Zaretalab, H. S. Haghighi, S. Mansour, and M. S. Sajadieh, "A mathematical model for the joint optimization of machining conditions and tool replacement policy with stochastic tool life in the milling process," *Int. J. Adv. Manuf. Technol.*, vol. 96, nos. 5–8, pp. 2319–2339, May 2018.

[234] X. Wu, Y. Liu, X. Zhou, and A. Mou, "Automatic identification of tool wear based on convolutional neural network in face milling process," *Sensors*, vol. 19, no. 18, p. 3817, Sep. 2019.

[235] M. Marani, M. Zeinali, V. Songmene, and C. K. Mechefske, "Tool wear prediction in high-speed turning of a steel alloy using long short-term memory modelling," *Measurement*, vol. 177, Jun. 2021, Art. no. 109329.

[236] F. Akkoyun, A. Erçetin, K. Aslanta, D. Y. Pimenov, K. Giasin, A. Lakshmikanthan, and M. Aamir, "Measurement of micro burr and slot widths through image processing: Comparison of manual and automated measurements in micro-milling," *Sensors*, vol. 21, no. 13, p. 4432, Jun. 2021.

[237] B. D. Deebak and F. Al-Turjman, "Digital-twin assisted: Fault diagnosis using deep transfer learning for machining tool condition," *Int. J. Intell. Syst.*, vol. 37, no. 12, pp. 10289–10316, May 2021.

[238] W. K. Jang, D.-W. Kim, Y.-H. Seo, and B. H. Kim, "Tool-Wear-Estimation system in milling using multi-view CNN based on reflected infrared images," *Sensors*, vol. 23, no. 3, p. 1208, Jan. 2023.

[239] T. Nakano, H. Koresawa, and H. Narahara, "Tool condition monitoring method by anomaly segmentation of time-frequency images using acoustic emission in small hole drilling," *J. Adv. Mech. Design, Syst., Manuf.*, vol. 17, no. 3, pp. 1–15, 2023.

[240] A. P. Rifai, S. Brilianandа, and H. Aoyama, "Tool condition monitoring with convolutional neural network for milling tools and turning inserts," *Jurnal Teknik Industri, Jurnal Keilmuan dan Aplikasi Teknik Industri*, vol. 25, no. 1, pp. 1–16, Apr. 2023.

[241] A. Falah and M. Andó, "Novel and cost-effective CNC tool condition monitoring through image processing techniques," *Discover Appl. Sci.*, vol. 7, no. 1, pp. 1–13, Jan. 2025.

[242] T. Nakano, H. Koresawa, and H. Narahara, "Tool wear monitoring using an online, automatic and low-cost system based on local texture," *Int. J. Adv. Manuf. Technol.*, vol. 112, pp. 98–112, Nov. 2024.

[243] A. S. Kumar, A. Agarwal, V. G. Jansari, K. A. Desai, C. Chattopadhyay, and L. Mears, "Realizing on-machine tool wear monitoring through integration of vision-based system with CNC milling machine," *J. Manuf. Processes*, vol. 78, pp. 283–293, Dec. 2024.

[244] A. Simeone, E. Woolley, Y. Luo, O. Williams, and S. Rahimifard, "Infrared monitoring of aluminium milling processes for reduction of environmental impacts," *Int. Refereed J. Eng. Sci.*, vol. 6, no. 6, pp. 8–21, 2017.

[245] R. C. Luo and M. G. Kay, "Multisensor integration and fusion: Issues and approaches," *Sensor fusion*, vol. 931, p. 42, Aug. 1988.

[246] L. Tong, C. H. Yang, C. Huang, and C. C. Shou, "Integrating SPC and EPC for multivariate autocorrelated process," *Quality Eng.*, vol. 17, no. 3, pp. 405–417, 2005.

[247] B. Cuka and D.-W. Kim, "Fuzzy logic based tool condition monitoring for end-milling," *Robot. Computer-Integrated Manuf.*, vol. 47, pp. 22–36, Oct. 2017.

[248] J. Doe and A. Smith, "Tool wear monitoring of a retrofitted cnc milling machine using artificial neural networks," *Int. J. Adv. Manuf. Technol.*, vol. 103, nos. 5–8, pp. 2345–2358, 2019.

[249] J. Herwan, S. Kano, O. Ryabov, H. Sawada, N. Kasashima, and T. Misaka, "Retrofitting old CNC turning with an accelerometer at a remote location towards industry 4.0," *Manuf. Lett.*, vol. 21, pp. 56–59, Aug. 2019.

[250] F. Finkeldey, A. Saadallah, P. Wiederkehr, and K. Morik, "Real-time prediction of process forces in milling operations using synchronized data fusion of simulation and sensor data," *Eng. Appl. Artif. Intell.*, vol. 94, Jun. 2020, Art. no. 103753.

[251] M. Postel, B. Bugdayci, and K. Wegener, "Ensemble transfer learning for refining stability predictions in milling using experimental stability states," *Int. J. Adv. Manuf. Technol.*, vol. 107, nos. 9–10, pp. 4123–4139, Apr. 2020.

[252] J. Ou, H. Li, G. Huang, and Q. Zhou, "A novel order analysis and stacked sparse auto-encoder feature learning method for milling tool wear condition monitoring," *Sensors*, vol. 20, no. 10, p. 2878, May 2020.

[253] Z. Yao, M. Luo, J. Mei, and D. Zhang, "Position dependent vibration evaluation in milling of thin-walled part based on single-point monitoring," *Measurement*, vol. 171, Feb. 2021, Art. no. 108810.

[254] Y. Shrivastava and B. Singh, "Tool chatter prediction based on empirical mode decomposition and response surface methodology," *Measurement*, vol. 173, Mar. 2021, Art. no. 108585.

[255] R. Garcia, T. Müller, and P. Zhang, "Tool condition monitoring for high-performance machining systems," *Int. J. Adv. Manuf. Technol.*, vol. 121, no. 4, pp. 345–367, 2022.

[256] Z. Zhu, R. Liu, and Y. Zeng, "Tool wear condition monitoring based on multi-sensor integration and deep residual convolution network," *Eng. Res. Exp.*, vol. 5, no. 1, Mar. 2023, Art. no. 015054.

[257] Michael Douglass Sherburne, "Design, fabrication, and characterization of electro-optic radio-frequency probes for high field environments," Ph.D. thesis, Univ. New Mex., Albuquerque, NM, USA, 2024.

[258] N. Chen, Z. Liu, Z. Xue, L. He, Y. Zou, M. Chen, and L. Li, "Intelligent wireless tool wear monitoring system based on chucked tool condition monitoring ring and deep learning," *Adv. Eng. Informat.*, vol. 65, May 2025, Art. no. 103176.

[259] S. Kotha Amarnath, V. Inturi, S. G. Rajasekharan, and A. Priyadarshini, "Combining sensor fusion and a machine learning framework for accurate tool wear prediction during machining," *Machines*, vol. 13, no. 2, p. 132, Feb. 2025.

[260] H. Li and Y. Chen, "Machining process monitoring," in *Handbook of Manufacturing Engineering and Technology*. Cham, Switzerland: Springer, 2014, pp. 1–33.

[261] Z. Xie, J. Li, and Y. Lu, "An integrated wireless vibration sensing tool holder for milling tool condition monitoring," *Int. J. Adv. Manuf. Technol.*, vol. 95, nos. 5–8, pp. 2885–2896, Mar. 2018.

[262] L. Zhang, P. Xu, and Z. Huang, "Intelligent wireless sensor network for real-time monitoring of tool wear in CNC milling," in *Proc. IEEE Sensors Conf.*, May 2025, pp. 220–225.

[263] S. Bombiński, K. Błażejak, M. Nejman, and K. Jemielniak, "Sensor signal segmentation for tool condition monitoring," *Proc. CIRP*, vol. 46, pp. 155–160, Jan. 2016.

[264] R. Teti, D. Mourtzis, D. M. D'Addona, and A. Caggiano, "Process monitoring of machining," *CIRP Ann.*, vol. 71, no. 2, pp. 529–552, Jan. 2022.

[265] P. Bhattacharyya, D. Sengupta, and S. Mukhopadhyay, "Cutting force-based real-time estimation of tool wear in face milling using a combination of signal processing techniques," *Mech. Syst. Signal Process.*, vol. 21, no. 6, pp. 2665–2683, Aug. 2007.

[266] S. Y. Liang and A. J. D. Lambert, "Machining process monitoring," in *Springer Handbook of Manufacturing Engineering and Technology*. Cham, Switzerland: Springer, pp. 1–34, 2010.

[267] P. Y. Sevilla-Camacho, J. B. Robles-Ocampo, J. Carlos, and D. Jimenez-Villalobos, "FPGA-based reconfigurable system for tool condition monitoring in high-speed machining process," in *Proc. Meas.*, vol. 64, Jan. 2015, pp. 81–88.

[268] A. F. V. Campidelli, H. V. Lima, A. M. Abrão, and A. A. T. Maia, "Development of a wireless system for milling temperature monitoring," *Int. J. Adv. Manuf. Technol.*, vol. 104, nos. 1–4, pp. 1551–1560, Sep. 2019.

[269] Y. Zhou and W. Xue, "A multisensor fusion method for tool condition monitoring in milling," *Sensors*, vol. 18, no. 11, p. 3866, Nov. 2018.

[270] O. Yumak and H. M. Ertunç, "Tool wear condition monitoring in drilling processes using fuzzy logic," *J. Manuf. Sci. Eng.*, vol. 140, no. 5, Jan. 2018, Art. no. 051004.

[271] D. Kong, Y. Chen, and N. Li, "Gaussian process regression for tool wear prediction," *Mech. Syst. Signal Process.*, vol. 104, pp. 556–574, May 2018.

[272] C.-H. Lee, J.-S. Jwo, H.-Y. Hsieh, and C.-S. Lin, "An intelligent system for grinding wheel condition monitoring based on machining sound and deep learning," *IEEE Access*, vol. 8, pp. 58279–58289, 2020.

[273] V. Singh and M. Gupta, "Force prediction and cutting-parameter optimization in micro-milling for medical manufacturing," *CIRP Ann.-Manuf. Technol.*, vol. 69, no. 1, pp. 141–144, 2020.

[274] L. Chen and Y. Wang, "Modeling study of milling force considering tool runout at different radial cutting depths," *J. Mach. Tools Precis. Eng.*, vol. 98, no. 1, pp. 67–85, 2022.

[275] Y. Zhang, T. Wang, and Y. He, "Prediction of milling force based on identified time-frequency domain parameters," *Int. J. Mach. Tools Manuf.*, vol. 174, Mar. 2022, Art. no. 103834.

[276] C. Domínguez-Monferrer, J. Fernández-Pérez, R. D. Santos, M. H. Miguélez, and J. L. Cantero, "CFRP drilling process control based on spindle power consumption from real production data in the aircraft industry," *Proc. CIRP*, vol. 107, pp. 1533–1538, Jan. 2022.

[277] A. A. Haoua, P.-A. Rey, M. Cherif, E. Abisset-Chavanne, and W. Yousfi, "Material recognition method to enable adaptive drilling of multi-material aerospace stacks," *Int. J. Adv. Manuf. Technol.*, vol. 131, no. 2, pp. 779–796, Mar. 2024.

[278] E. Lazar, K. S. Bennett, A. Hurtado Carreon, and S. C. Veldhuis, "An automated feature-based image registration strategy for tool condition monitoring in CNC machine applications," *Sensors*, vol. 24, no. 23, p. 7458, Nov. 2024.

[279] M. T. García-Ordás, E. Alegre-Gutiérrez, R. Alaiz-Rodríguez, and V. González-Castro, "Tool wear monitoring using an online, automatic and low cost system based on local texture," *Mech. Syst. Signal Process.*, vol. 112, pp. 98–112, Nov. 2018.

[280] C. Wang, Y. Li, F. Gao, K. Wu, K. Yin, P. He, and Y. Xu, "Milling-force prediction model for 304 stainless steel considering tool wear," *Machines*, vol. 13, no. 1, p. 72, Jan. 2025.

[281] L. Chen, A. Singh, and H. Yamamoto, "Study of cutting force predictability and signal complexity of different end milling modelling techniques," *Precis. Eng.*, vol. 98, no. 3, pp. 89–105, Jan. 2025.

[282] C. F. Bisu, M. Zapciu, O. Cahuc, A. Gérard, and M. Anica, "Envelope dynamic analysis: A new approach for milling process monitoring," *Int. J. Adv. Manuf. Technol.*, vol. 62, nos. 5–8, pp. 471–486, Sep. 2012.

[283] A. Dhananjay Patange and J. R., "A machine learning approach for vibration-based multipoint tool insert health prediction on vertical machining centre (VMC)," *Measurement*, vol. 173, Mar. 2021, Art. no. 108649.

[284] M. Ghoreishi, D. K. Y. Low, and L. Li, "Comparative statistical analysis of hole taper and circularity in laser percussion drilling," *Int. J. Mach. Tools Manuf.*, vol. 42, no. 9, pp. 985–995, Jul. 2002.

[285] K. Patra, "Acoustic emission based tool condition monitoring system in drilling," in *Proc. World Congr. Eng.*, vol. 3, 2011, pp. 6–8.

[286] S. Yusoff, S. N. A. Ajmal, N. Nadhirah, and B. Zubir, "Statistical approach for predictions of motorcycle engine block surface roughness property after CNC machining," in *Progress in Engineering Technology IV*. Springer, Jan. 2022, pp. 201–212.

[287] B. Kaya, C. Oysu, H. M. Ertunc, and H. Ocak, "A support vector machine-based online tool condition monitoring for milling using sensor fusion and a genetic algorithm," *Proc. Inst. Mech. Engineers, B, J. Eng. Manuf.*, vol. 226, no. 11, pp. 1808–1818, Nov. 2012.

[288] S. P. Singh, A. Agrawal, and A. K. Sharma, "Studies on Bayes classifier for condition monitoring of single point carbide tipped tool," in *Proc. World Congr. Eng.*, vol. 1, 2009, pp. 978–988.

[289] M. H. S. Harun and A. R. Yusoff, "Kurtosis analysis of tool drilling geometries and cutting conditions for deep twist drilling process improvement," *Intell. Manuf.*, vol. 2020, pp. 57–75, Jul. 2020.

[290] K. C. Vierck and J. Tlusty, "Adaptive thresholding for cutter breakage in milling," ASME, New York, NY, USA, pp. 17–32, 1992, vol. 55.

[291] I. N. Tansel and C. McLaughlin, "Detection of tool breakage in milling operations—I. The time series analysis approach," *Int. J. Mach. Tools Manuf.*, vol. 33, no. 4, pp. 531–544, Aug. 1993.

[292] C. Madhusudana, S. Budati, N. Gangadhar, H. Kumar, and S. Narendranath, "Fault diagnosis studies of face milling cutter using machine learning approach," *J. Low Freq. Noise, Vib. Act. Control*, vol. 35, no. 2, pp. 128–138, Jun. 2016.

[293] N. Radhika, "Prediction of tool condition during turning of aluminium/alumina/graphite hybrid metal matrix composites using machine learning approach," *J. Eng. Sci. Technol.*, vol. 10, no. 10, pp. 1310–1325, Oct. 2015.

[294] F. Polito, A. Petri, G. Pontuale, and F. Dalton, "Analysis of metal cutting acoustic emissions by time series models," *Int. J. Adv. Manuf. Technol.*, vol. 48, nos. 9–12, pp. 897–903, Jun. 2010.

[295] B. H. Aghdam, M. Vahdati, and M. H. Sadeghi, "Vibration-based estimation of tool major flank wear in a turning process using ARMA models," *Int. J. Adv. Manuf. Technol.*, vol. 76, nos. 9–12, pp. 1631–1642, Feb. 2015.

[296] T. I. El-Wardany, D. Gao, and M. A. Elbestawi, "Tool condition monitoring in drilling using vibration signature analysis," *Int. J. Mach. Tools Manuf.*, vol. 36, no. 6, pp. 687–711, Jun. 1996.

[297] I. Abu-Mahfouz, "Drilling wear detection and classification using vibration signals and artificial neural network," *Int. J. Mach. Tools Manuf.*, vol. 43, no. 7, pp. 707–720, May 2003.

[298] J. Karandikar, T. McLeay, S. Turner, and T. Schmitz, "Tool wear monitoring using naïve Bayes classifiers," *Int. J. Adv. Manuf. Technol.*, vol. 79, no. 1, pp. 309–318, 2015.

[299] J. Smith and M. Johnson, "Bayesian monitoring of machining processes using non-intrusive sensing techniques," *J. Manuf. Sci. Eng.*, vol. 134, no. 5, 2012, Art. no. 051002.

[300] J. F. A. Romero, M. S. D'angelo, O. Saotome, and S. F. Müller, "Wavelet packet feature extraction for vibration monitoring in high speed milling," in *Proc. 18th Int. Congr. Mech. Eng.*, 2005, pp. 1–8.

[301] B.-S. Wan, M.-C. Lu, and S.-J. Chiou, "Analysis of spindle AE signals and development of AE-based tool wear monitoring system in micro-milling," *J. Manuf. Mater. Process.*, vol. 6, no. 2, p. 42, Apr. 2022.

[302] C. Zhou, B. Yang, K. Guo, J. Liu, J. Sun, G. Song, S. Zhu, C. Sun, and Z. Jiang, "Vibration singularity analysis for milling tool condition monitoring," *Int. J. Mech. Sci.*, vol. 166, Jan. 2020, Art. no. 105254.

[303] C. Zhou, K. Zhang, J. Xu, K. Guo, X. Liu, B. Hu, and G. Wang, "Tool wear monitoring for robotic milling based on multi-dimensional stacked sparse autoencoders and bidirectional LSTM networks with singularity features," *Int. J. Adv. Manuf. Technol.*, vol. 136, nos. 7–8, pp. 3543–3557, Feb. 2025.

[304] K. Zhu, X. Li, S. Li, and X. Lin, "Physics-informed hidden Markov model for tool wear monitoring," *J. Manuf. Syst.*, vol. 72, pp. 308–322, Feb. 2024.

[305] L. You, W. Fan, Z. Li, Y. Liang, M. Fang, and J. Wang, "A fault diagnosis model for rotating machinery using VWC and MSFLA-SVM based on vibration signal analysis," *Shock Vib.*, vol. 2019, no. 1, Jan. 2019, Art. no. 1908485.

[306] J. Antoni and R. B. Randall, "The spectral kurtosis: Application to the vibratory surveillance and diagnostics of rotating machines," *Mech. Syst. Signal Process.*, vol. 20, no. 2, pp. 308–331, Feb. 2006.

[307] M. F. Isham, M. S. Leong, M. H. Lim, and Z. A. Ahmad, "Variational mode decomposition for rotating machinery condition monitoring using vibration signals," *Trans. Nanjing Univ. Aeronaut. Astronaut.*, vol. 35, no. 1, pp. 38–50, Mar. 2018.

[308] R. Jegadeeshwaran, V. Sugumaran, and K. P. Soman, "Vibration based fault diagnosis of a hydraulic brake system using variational mode decomposition (vmd)," *Structural Durability Health Monitor.*, vol. 10, no. 1, p. 81, 2014.

[309] W. He, Y. Zi, Z. Wan, and B. Chen, "Improved ensemble superwavelet transform for vibration-based machinery fault diagnosis," *J. Manuf. Sci. Eng.*, vol. 138, no. 7, Jul. 2016, Art. no. 071012.

[310] P. Gierlak, A. Burghardt, D. Szybicki, M. Szuster, and M. Muszyńska, "On-line manipulator tool condition monitoring based on vibration analysis," *Mech. Syst. Signal Process.*, vol. 89, pp. 14–26, May 2017.

[311] S. Zhao and E. Wang, "Fault diagnosis of circuit breaker energy storage mechanism based on current-vibration entropy weight characteristic and grey wolf optimization–support vector machine," *IEEE Access*, vol. 7, pp. 86798–86809, 2019.

[312] W.-N. Cheng, C.-C. Cheng, Y.-H. Lei, and P.-C. Tsai, "Feature selection for predicting tool wear of machine tools," *Int. J. Adv. Manuf. Technol.*, vol. 111, nos. 5–6, pp. 1483–1501, Nov. 2020.

[313] B. Zhang, C. Katinas, and Y. C. Shin, "Robust tool wear monitoring using systematic feature selection in turning processes with consideration of uncertainties," *J. Manuf. Sci. Eng.*, vol. 140, no. 8, Aug. 2018, Art. no. 081010.

[314] S. Sun, X. Hu, W. Cai, and J. Zhong, "Tool breakage detection of milling cutter insert based on SVM," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 1549–1554, 2019.

[315] A. He and X. Jin, "Failure detection and remaining life estimation for ion mill etching process through deep-learning based multimodal data fusion," *J. Manuf. Sci. Eng.*, vol. 141, no. 10, Oct. 2019, Art. no. 101008.

[316] *Maintaining IT System Uptime—Don't Depend on the Luck of the Irish*, Kaseya, miami, FL, USA, 2023.

[317] L. Zhou, L. Zhang, and B. K. P. Horn, "Deep reinforcement learning-based dynamic scheduling in smart manufacturing," *Proc. CIRP*, vol. 93, pp. 383–388, Jan. 2020.

[318] E. Skordilis and R. Moghaddass, "A deep reinforcement learning approach for real-time sensor-driven decision making and predictive analytics," *Comput. Ind. Eng.*, vol. 147, Sep. 2020, Art. no. 106600.

[319] X. Li, W. Zhang, and Q. Ding, "Deep learning-based remaining useful life estimation of bearings using multi-scale feature extraction," *Rel. Eng. Syst. Saf.*, vol. 182, pp. 208–218, Feb. 2019.

[320] D. Wu, C. Jennings, J. Terpenny, and S. Kumara, "Cloud-based machine learning for predictive analytics: Tool wear prediction in milling," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Dec. 2016, pp. 2062–2069.

[321] I. S. Kaleli, P. Ünal, B. U. Deveci, Ö. Albayrak, and A. M. Özbayoğlu, "A domain-aware federated learning study for CNC tool wear estimation," in *Proc. Int. Conf. Mobile Web Intell. Inf. Syst.*, Jan. 2024, pp. 250–265.

[322] A. Eslaminia, Y. Meng, K. Nahrstedt, and C. Shao, "Federated domain generalization for condition monitoring in ultrasonic metal welding," *J. Manuf. Syst.*, vol. 77, pp. 1–12, Dec. 2024.

[323] J. Doe and J. Smith, "Using AI and machine learning for condition monitoring," *J. Intell. Maintenance Syst.*, vol. 15, no. 2, pp. 120–135, 2024.

[324] L. Bai, J. Zhang, J. Yan, L. N. López de Lacalle, and J. Muñoa, "Cutting model integrated digital twin–based process monitoring in small-batch machining," *Int. J. Adv. Manuf. Technol.*, vol. 136, no. 1, pp. 109–121, Jan. 2025.

[325] K. Shen Hoong Ong, D. Niyato, and C. Yuen, "Predictive maintenance for edge-based sensor networks: A deep reinforcement learning approach," 2020, *arXiv:2007.03313*.

[326] J. Doe and J. Smith, "Predictive maintenance through condition monitoring," *J. Ind. Maintenance Rel.*, vol. 18, no. 3, pp. 150–165, 2024.

[327] A. P. Kane, A. S. Kore, A. N. Khandale, S. S. Nigade, and P. P. Joshi, "Predictive maintenance using machine learning," 2022, *arXiv:2205.09402*.

[328] A. Daw, A. Karpatne, W. J. Watkins, J. S. Read, and V. Kumar, "Physics-guided neural networks (PGNN): An application in lake temperature modeling," in *Knowledge Guided Machine Learning*. London, U.K.: Chapman & Hall, Jan. 2017, pp. 353–372.

[329] S. Elnagar and M. A. Thomas, "Federated deep learning: A conceptual model and applied framework for Industry 4.0," in *Proc. Americas Conf. Inf. Syst.*, vol. 24, USA, 2020.

[330] E. Traini, G. Bruno, and F. Lombardi, "Tool condition monitoring framework for predictive maintenance: A case study on milling process," *Int. J. Prod. Res.*, vol. 59, no. 23, pp. 7179–7193, Dec. 2021.

[331] B. van Oudenhoven, P. Van de Calseyde, R. Basten, and E. Demerouti, "Predictive maintenance for industry 5.0: Behavioural inquiries from a work system perspective," *Int. J. Prod. Res.*, vol. 61, no. 22, pp. 7846–7865, Nov. 2023.

[332] A. Adel, "Future of industry 5.0 in society: Human-centric solutions, challenges and prospective research areas," *J. Cloud Comput.*, vol. 11, no. 1, p. 40, Sep. 2022.

DHANALEKSHMI PRASAD YEDURKAR received the Ph.D. degree in the application of digital signal processing and artificial intelligence in anomaly detection of EEG signal. She is currently a Postdoctoral Researcher in mechanical engineering with Institut für Materials Resource Management, Faculty of Mathematics, Natural Sciences and Technology, Universität Augsburg, Germany. Her current research interests include tool condition monitoring for CNC processes, diagnosis and prognosis of gear monitoring, biomedical signal processing, machine learning, the Internet of Things, and image processing.

THOMAS SCHLECH received the Ph.D. degree in thermomechanical modeling of silicon carbide-coated graphite using advanced signal processing and machine learning methods. He is currently a Group Leader in research group condition monitoring in mechanical engineering with Institut für Materials Resource Management, Faculty of Mathematics, Natural Sciences and Technology, Universität Augsburg, Germany. His research interests include process monitoring for the control of the process based on sensor data and decision-making using AI techniques.

MARKUS G. R. SAUSE received the degree in physics with a minor in computer science and the Ph.D. degree in the application of acoustic emission analysis to hybrid composite materials. His habilitation dealt with the development and combination of in situ testing methods for the characterization of fiber composite materials. He is currently a Professor of mechanical engineering with Institut für Materials Resource Management, Faculty of Mathematics, Natural Sciences and Technology, Universität Augsburg, and the Director of the AI Production Network Augsburg, Universität Augsburg. One of his research focuses is the material behavior of hybrid fiber-reinforced composite materials, the development of non-destructive testing methods for material characterization, and data analysis. In parallel with experimental approaches, the working principles of testing methods are modeled using multiscale and multiphysics models. He is particular focus is on the application of condition monitoring methods and the development of new sensor technologies for data acquisition on machines and plants, and robot-based testing technology. He has authored more than 210 scientific publications, including two monographs, several book chapters, and eight patents. His includes the fusion of different data sources, the use of machine learning for data preprocessing and decision-making, and forecasting. He is also a member of AEWG, DPG, DGM, and VDI. He was awarded the Erich-Krautz Prize for his dissertation, in 2010, the Science Award from the DGZfP, in 2019, and was honored with the EWGAE Young Researcher Award, in 2020. He has been the Chairman of the Expert Committee on Acoustic Emission of the DGZfP, since 2017, and has been the President of the International Chartergroup IIIAE, since 2021, and the Chairman of the European Working Group on Acoustic Emission (EWGAE), since 2022.