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FPGA AND MACHINING PROCESS - A REVIEW ON PERFORMANCE AND APPLICATIONS

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ABSTRACT

Machining procedures should deal with contortions of work pieces, machine tools and cutters, that are created by chatter vibration, thermal effect and cutting force. Excellent performance of these sophisticated procedures relies on information availability regarding process conditions. There is a need for dependable systems that integrate signal processing techniques for gleaning useful information. These are useful in the precise machining process, which requires the tightest of tolerances. Machine performance control and prediction become particularly challenging in such conditions of extreme change. Thus, for identifying the actual tool health, a process monitoring or Tool Condition Monitoring (TCM) system is required for various machining processes. Knowledge of tool state or information regarding its condition during machining operations aids in taking relevant actions for effectively performing machining tasks. This paper explores the studies on TCM and investigates the diverse parameters and techniques exploited for TCM in distinct machining operations. This article provides the necessity and significance of FPGA-based monitoring mechanisms for TCM. It investigates the studies on FPGA-based performance monitoring systems utilized for diverse tasks and applications and elucidates the role of FPGA-based performance monitoring systems for developing better and effective future TCM systems useful in diverse machining tasks.

Keywords: *FPGA, Machining Process, Performance Monitoring, TCM, Tool Wear.*

1. INTRODUCTION

Recently, High-speed machining (HSM) is the prevalent improved manufacturing technology. Owing to general usage of Computer Numerical Control (CNC) machine tools together with well-performing Computer Aided Design (CAD) systems, HSM has provided various advantages compared to classical machining methods with regard to productivity, quality, etc. Therefore, HSM is popularly exploited in manufacturing procedures. During HSM procedure, the operators largely focus on testing operation sequences, peripheral failures, machine tool and tool conditions (breakage or wear) etc. They are also responsible for taking correct measures for adjusting speeds and operation sequences in real-time. Maximizing the tool's operating time and maintaining tools from damage is linked directly to its performance optimization. Tool wear generally occurs by amalgamation of several phenomena. It can happen slowly or in extreme breakdowns. Slow wear might occur through diffusion or abrasion, and adhesion. However, monitoring such tool wear events is not so simple in machining procedures. The condition monitoring of machine processes can be classified into three crucial categories, namely tool wear, chatter and tool condition monitoring (TCM) [1]. The quantity of research conducted on machine process condition monitoring is depicted in Fig 1. Many studies have focused on TCM and tool wear, because terrific tool states are imperative for eliminating vibrations leading to chatter problems and for providing supreme quality products.

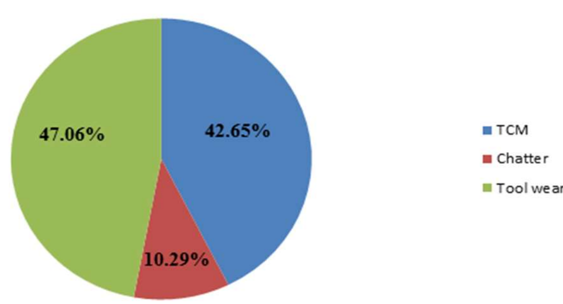

Figure 1:Research conducted on machine process condition monitoring [1].

In HSM, TCM is a vital subject of concern. Malfunction of tools leads to interruption of entire production and causes terrific financial losses. Tool breakage during machining procedure causes damage which negatively effects the integrity and quality of machined regions or surfaces. Doubtlessly, determining the occurrence of tool breakage or need for its replacement is crucial. If tool wear or breakage is not timely detected, it will cause severe effects on workpiece quality. TCM is crucial for acquiring better quality product. It has become imperative to automated machining, smart manufacturing and diverse industrial processes. The prime thought behind TCM is to track the tool's health condition continuously. Through an effective TCM, scrapped components, unexpected downtime and machine tool damages could be prevented. Typically an improved TCM system comprises monitor, signal amplifiers/conditioners and sensors. Sensors are placed close to the desired tool's tip. Signal processing operations are performed for acquiring the required data from signals through respective sensors. The signals thus received from sensors are analyzed on the monitor (or display unit). TCM methods can be of two types namely indirect and direct. Direct scheme is implemented through utilizing optical gadgets for estimating the wear region's geometry. It consumes a longer time Indirect scheme is dependent mainly on the acquirement of estimated parameters of process (such as the vibration, change of workpiece size, temperature, cutting force, motor current, surface roughness and acoustic emission) and also the correlation between these parameters and tool wear [2]. Indirect TCM systems involve data collection from signals through sensors, signal processing and relevant feature extraction from acquired signals, estimation or categorization of tool state through pattern recognition, regression analysis neural networks, fuzzy logic and other classification schemes and finally tool condition/state detection. The TCM system's block diagram is depicted in Fig 2. Indirect techniques support on-line TCM without affecting production rate.

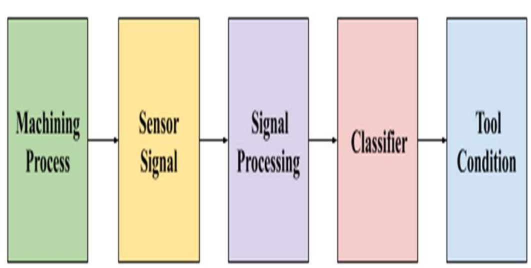

Figure 2:Indirect TCM system [3].

At the time of machining procedure, tool breakage occurs. Not detecting such tool wear during the HSM process, might deteriorate production performance owing to its effect on production costs and work piece quality. However, certain monitoring systems are devised and reported to identify the operating condition of tools in HSM. These TCM systems are dependent on calibration of physical parameters pertinent to cutting tool settings such as spindle and feed motor currents [4], [5], cutting force [6], [7] and vibration [8], [9]. Nonetheless, few of these TCM systems possess drawbacks for their commercial application including huge costs, operation with confined characteristics or complex deployment on machine tool. These drawbacks are especially owing to utilized sensors and types of calibrated parameters. For instance, calibration of cutting force through dynamometers. As these sensors are fixed between machining table and workpiece, placing them on machine tool is difficult and further restricts the optimum workpiece size. The other instance can be current signal acquired through monitoring the servo drivers output. These drivers comprise band-limited current sensors. Therefore, TCM in ranges exceeding the band coverage limits of these sensors can be infeasible. Thus, contrary to afore-listed parameters, vibration signal provides the finer characteristics like a) enough data about tool condition, b) periodic shape which matches the cutting force, c) applicability, d) reliability, e) simpler measurement implementation i.e. without involving any modification in machine tool, f) low-cost, and g) robustness. Because of this, vibration signal has been utilized for TCM in classical machining [10], [11], [12], [13]. Vibration analysis is chiefly employed for detecting tool condition, dimensional deviations, surface quality and chatter events in machining tasks. Usually, vibration amplitude produced through interaction of workpiece and new tool is smaller than that of worn tool.

Many previously reported systems for TCM are devised for inflexible cutting conditions. Although, in the commercial world, the machining procedures are executed under varying cutting conditions. Thus, a substantial characteristic which should be taken into account in the TCM system design is its easy and rapid adaptation to diverse cutting variables set by system operators. Some systems utilize lower processing speed and incompatible methods for analysis. Utilization of such inappropriate methods for system analysis might degrade the essential improvements needed in TCM systems, thereby limiting their production performance. Few of the systems employ fast fourier transform (FFT) for analysis; although the efficacy of such signal spectral scrutiny is limited because of the perplexity of the cutting procedure, particularly for disturbed milling process. In such events, dynamic signals are non-stationary and non-linear [14] and therefore, non-linear and transient signals cannot be determined on FFT basis as they present inter-modulation or harmonic distortions. Moreover, such method needs longer time and more power consumption. Thus, FFT method is not so qualified for processing machining signals. The TCM system implementation (hardware/software) is also a matter of concern. Many TCM systems also encounter issues in hardware or software implementation which contribute towards rising expenses and performance reduction.

Thus, to surmount all the above-mentioned problems, a reliable and effective system is desired for indicating and detecting the essential tool conditions in real-time and online in HSM processes. Optimum machining process performance largely relies on information availability regarding process conditions necessary for monitoring the process and providing the desired feedback to the controller. In automation of machine tool, tool health plays a pivotal role and therefore online TCM is of huge industrial interest. Recently, Field Programmable Gate Array (FPGA) based TCM systems have gained massive popularity because of their potential in real-time and online monitoring. FPGA-based TCM systems can be used for signal acquisition, monitoring and conditioning in numerous machining processes [15]. They are proven to deliver effective outcomes for TCM in laboratories and industrial processes. Moreover, they are scalable and reconfigurable and thus are adaptable to miscellaneous conditions.

This paper delves into TCM research and examines the many characteristics and methods used for TCM in various machining processes. The importance and relevance of FPGA-based monitoring techniques for TCM are outlined in this paper. It examines research on FPGA-based performance monitoring systems used for various jobs and applications, and it clarifies the significance of such systems in the design of more effective and efficient future TCM systems for use in a wide range of machining applications.

1.1 Paper Organization

Section I provides the significance and necessity of TCM in machining processes. It elucidates the prominence of FPGA-based performance monitoring systems in TCM. Section II surveys the studies on TCM. Section III reviews the studies on FPGA-based performance monitoring systems employed for diverse tasks and applications. Section IV explains the role of FPGA in TCM. Section V provides the vital findings of this study.

2. LITERATURE SURVEY

Despite the several changes in information collection techniques over the time, the methodology followed in the past for TCM continues to be the same. The past methodologies for TCM involve signal acquisition, filtering and decision making procedures. Initially, signals are acquired using distinct sensors and are filtered for discarding noise and irrelevant information using feature extraction techniques. Finally, through detection or categorization processes, tool conditions are determined. In present TCM methodologies, control systems are integrated along with signal acquisition, filtering and decision making systems. Figure 3 depicts the past and current methodologies followed in TCM. In current methodologies, Wireless Sensor Networks (WSN) are integrated into classical machines for wireless information acquisition and transfer followed by signal filtering, processing, detecting or categorizing procedures. Additionally, control systems are employed for controlling the worst conditions of HSM operations through self-adjusting machine parameters, fixing the loosed components/parts and stopping the operation if required. These procedures are intelligently performed using advanced techniques for attaining better quality products.

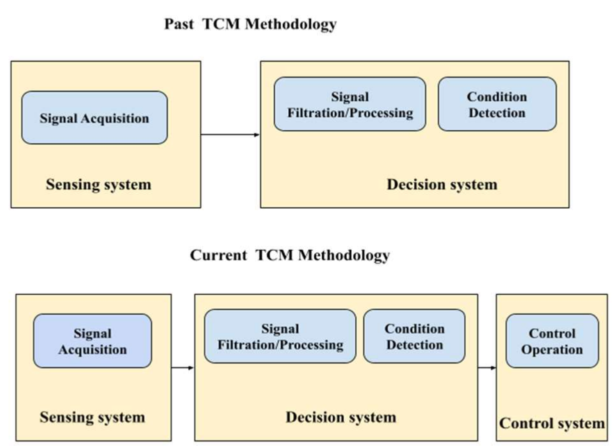

Figure 3:Past and current methodology for TCM

In this section numerous studies on TCM based on sensors, feature extraction techniques and monitoring frameworks employed are explored.

2.1 Sensors

In TCM, diverse sensors are utilized for acquiring signals required for determining the machine tool state. In some studies, TCM is performed using a single sensor while in others multiple sensors are used. In the present survey, single sensor studies focusing on motor current, vibration, cutting force and Acoustic Emission (AE) sensors are explored and multiple sensor studies focusing on combinations of diverse sensors are investigated.

2.1.1. Single sensor:

- Motor current: Motor current sensors are rated as more appropriate for manufacturing environments than cutting force sensors owing to their simple application and lack of deployment effects on machining procedures [4], [16], [17]. In [4], a simple, rapid and effective approach for tool breakage identification in CNC HSM process was discussed. The efficacy of this approach relied on estimation of current signals of feed-motor using cost-effective sensor. It estimated the difference between current consumption variations during abnormal (tool breakage) and normal tool operating conditions. In this work, feed-motor current was directly applied for tool breakage recognition. In [18], it was observed that motor current signals strongly correlated with tool wear compared to vibration signals and were less sensitive to noise thereby leading to more precise tool state detection. However, in [19], the research illustrated that the motor current was insensitive to variations in the cutting force at huge motor frequencies, thus indicating that motor current signal was inappropriate for TCM at greater spindle speeds. The workpiece materials and tools used and HSM operations performed during motor current monitoring for TCM are depicted in Table 1.

Table 1: Motor current monitoring

References	Workpiece material	Tool used	Monitoring target	HSM operation
[4]	Aluminium alloy 6061-T6	Carbide face mill	Diagnosis	Face milling
[17]	Aluminium alloy	Seco cutter	Diagnosis	Milling
[19]	S45C steel	4-fluted end mill	Diagnosis	End milling

- Vibration: Vibration sensors are largely utilized in TCM as they are simple to install and inexpensive [20], [21]. In [10], a TCM through vibration features in a turning process was discussed. In this study, time domain attributes were viewed to be largely vulnerable to cutting condition compared to tool wear while the frequency attributes matched well with tool wear. Results highlighted that attributes of vibration signals were effective in cutting TCM. In [11], the correlation between tool wear and vibration during milling was explained. In this work, vibration was measured merely in the direction having large dominant signals (i.e. machining direction) instead of other directions. Toolmaker's microscope was utilized for determining the tool wear. This study depicted that vibration amplitude increased with the increased tool wear. In [12], an approach was discussed for TCM in end-milling process based on collected vibration signal through a data acquisition unit. In this approach, frequency peaks and vibration amplitudes (time domain) were utilized as significant attributes for TCM. In [22], TCM in micro-milling procedure through vibration signals was discussed. Vibration signals during cutting procedure were collected from three directions through an accelerometer and frequency domain attributes indicating changes in wear were chosen based on mean scatter criteria. It illustrated that for TCM, combining signals from two directions provided a better categorization rate than identifying its condition through a unidirectional sensor. In [23], TCM in milling operation was discussed. Vibration analysis was performed for determining the cutting tool's state. Traditional processing techniques were applied to vibrations resulting from cutting procedures for acquiring tool condition data. This work stated that vibration signal's amplitude considerably increased when tool was severely impaired by wear. In [24], vibration signals were used for monitoring the face milling equipment's condition. Milling tool's vibration signals were obtained under healthy/normal and faulty conditions for determining the tool state. The distinct tool states like chipping, breakage, flank wear and healthy states were detected. The vibration amplitude analogous to fault state showed slight variation when compared to normal state of tool. Though vibration signals are useful for TCM, they are hard to filter and thus provide erroneous information [25].The workpiece materials and tools used and HSM operations performed during vibration monitoring for TCM are depicted in Table 2.

Table 2:Vibration monitoring

References	Work piece material	Tool used	Monitoring target	HSM operation
[10]	EN24 BS 970	End mill cutter	Diagnosis	End milling
[11]	AISI D3 steel	End mill cutter	Diagnosis	End milling
[12]	Steel alloy	End mill cutters	Diagnosis	End milling
[22]	SK2 steel	Micro-end mill	Diagnosis	End milling
[23]	Mild steel	Four-fluted end mill	Diagnosis	End milling
[24]	42CrMo4 steel alloy	Carbide face milling cutter	Diagnosis	Face milling
[56]	Titanium alloy	Milling cutter	Diagnosis	Milling
[59]	42CrMo4 steel alloy	Carbide face milling cutter	Diagnosis	Face milling
[60]	Mild steel	Carbide cutter	Diagnosis	Milling

- Cutting force Cutting force is highly sensitive to variations in tool state and thus could be employed for precisely estimating the tool state [26], [27]. In [28], real time TCM in milling was discussed through tracking force coefficients during cutting procedure. In milling procedure tool wear was determined through utilizing cutting force parameter as monitoring signal. The radial and tangential cutting force parameters were traced for monitoring wear. Numerous experiments with distinct workpiece materials were conducted for inspecting the proposed TCM system's feasibility. This approach was supportive in detecting the transition from slight wear area to failure area wherein the wear rate accelerated. In [29], TCM in micromachining was discussed. This study performed TCM through estimating the mean cutting force. It revealed that cutting force variations enhanced steadily during machining procedures. This work highlighted that for accurate tool condition estimation, measurement of thrust and feed cutting forces at similar cutting conditions was important. Results illustrated that cutting force characteristics largely influenced tool condition estimation. In [30], cutting force based piezoelectric dynamometer was employed for TCM in milling operation. Though cutting force dependent sensors are helpful in TCM, they are sophisticated to implement in industrial conditions as their physical characteristics limit the workpiece size thus making it inappropriate for milling large and medium worpieces [31]. The workpiece materials and tools used and HSM operations performed during cutting force monitoring for TCM are depicted in Table 3.

Table 3:Cutting force monitoring

References	Workpiece material	Tool used	Monitoring target	HSM operation
[27]	TC21 titanium alloy	Seco milling cutter	Diagnosis	Milling
[28]	Steel 1018, Aluminium 6061 and Inconel	End mill	Diagnosis	End milling
[29]	Aluminium, steel	Carbide end-mill	Diagnosis	End milling
[30]	Steel 1018	Four-fluted end milling cutter	Diagnosis	End milling
[61]	Inconel 718	Three-fluted base nose cutter	Diagnosis	Milling
[62]	ASSAB 718HH	Milling cutter	Diagnosis and prognosis	Milling

- AE: AE sensors are specifically suitable for TCM in HSM processes like milling as the signals acquired through these sensors are undisturbed mechanically and exhibit superior sensitivity than vibration signals and cutting force [32], [33]. In [34], an experiment for tool wear estimation was conducted using AE signals. Depending on the outcomes, maximum cutting parameters were chosen for minimal tool wear. In [35], acoustic emission (AE) signals were employed for tool wear monitoring during machining operation. The signals acquired contained a frequency level ranging between 100-2 MHz. The TCM had a crucial impact above 200kHz. The gradual progression of tool breakage was indicated by RMS

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values of AE. Tool breakage was analyzed through capturing signals from transducer. Based on RMS values, the tool breakage was predicted. In [36], a methodology for monitoring drilling tool's condition was presented. For TCM, AE signals during drilling were acquired, filtered and analyzed for extracting attributes that were vulnerable to wear at diverse cutting conditions. In [37], tool breakage evaluation through monitoring AE signals in drilling was discussed. The dependency between AE signals and torque was analyzed and their effects on drill wear were studied. The work revealed that AE signals largely influenced tool wear. In [38], AE signals were captured and its features like amplitude, signal level, etc. were extracted and analyzed for TCM in cylindrical grinding procedure. Good and dull states of grinding tool were predicted. The study indicated that a robust correlation between surface roughness and AE signals produced by grinding procedure largely influenced the grinding tool's condition. Though AE sensors are helpful in TCM, they are extremely sensitive to noise and thus enhance the complexity of extracting the desired signal feature data [39]. The workpiece materials and tools used and HSM operations performed during AE signal monitoring for TCM are depicted in Table 4.

Table5: AE signal monitoring

References	Workpiece material	Tool used	Monitoring target	HSM operation
[32]	SK2 steel	End mill	Diagnosis	End milling
[33]	Steel 1035	Seco carbide cutter	Diagnosis	Milling
[35]	C45 steel	TK35 rough turning tool	Prognosis	Turning
[36]	Mild steel	Two-fluted twist drill	Prognosis	Drilling
[37]	SAE 1040 steel	Twist drill	Diagnosis	Drilling
[38]	Mild steel	Aluminum oxide grinding wheel	Diagnosis	Grinding

- Temperature: High temperatures generally contribute to abnormalities in HSM operations. The elevated temperature while machining tasks leads to tool wear, increased cost and workpiece quality degradation. In [40], temperature sensor was applied for TCM. The temperature increase was measured through k-type thermocouple. The direct effect of diverse machining variables with temperature increase was analyzed. In [41] and [42], temperature sensors were deployed on diverse machining components for effective TCM through facilitating temperature monitoring. The workpiece materials and tools used and HSM operations performed during temperature monitoring for TCM are depicted in Table 5.

Table 5:Temperature monitoring

References	Workpiece material	Tool used	Monitoring target	HSM operation
[40]	Al 6063	End mill cutter	Prognosis	End Milling
[41]	-	-	Diagnosis	Milling
[42]	-	-	Diagnosis	Milling

2.1.2. Multiple sensors

Owing to the limitations encountered in single sensor based TCM methods, multiple sensor based TCM approaches have been exploited. In [9], multi-modal sensing comprising dynamometer, emission sensor and accelerometer was employed for monitoring the HSM process. The tool breakage was determined from the shift in signal's energy distribution from low to high frequency. In [43], multisensor fusion dependent TCM system design was presented for TCM in milling operation. Multiple sensors examined in the study included spindle power, AE, force and vibration sensor for frequency and time domain information. This work focused on robustness and accuracy of tool state categorization for distinct sensor combinations, fusion methods and prediction algorithms. Experimental outcomes indicated that feature level-based TCM system design significantly enhanced the tool state categorization accuracy and combination of multi-sensors with correlation-dependent feature selection technique and machine ensemble method ensured better TCM. In [44], TCM was performed through combining AE signals, adaptive thresholding and motor current. Tool deterioration procedure was investigated through conducting tool durability tests. Adaptive thresholding and motor current methods reasonably performed well in detection of tool wear degradation during roughing process while AE signals performed well during finishing process. AE signals provided comprehensive tool condition data regarding crack propagation, serious adhesive wear and tool edge wear. The TCM system employed in proposed study showed excellent potential in preventing surface irregularities and disastrous tool failures. In [45], a multisensor data fusion approach was presented for TCM. Cutting sound and AE were utilized for monitoring. The study outcomes suggested that joint decision (decision using AE and decision using cutting sound) was better than separate decision for tool condition categorization and wear quantity prediction. However, need of improving proposed TCM system was suggested as joint decision outputs contained few prediction errors and misclassification problems. In [46], several sensor information like power data, cutting force and vibration data were collected for effective TCM and tool life prediction. This work also revealed the relation between tool wear and machining parameters. The employed sensors exhibited good potential in capturing the tools' status. In [47], TCM was accomplished through acquiring numerous signals from machining zone namely spindle vibration, sound pressure, cutting force and spindle current. These signals were blended for estimating flank wear. In [48], TCM was achieved using multisensors. For deciding the tool status, signals gained from numerous sensors were processed. For TCM, parameters like cutting sound, cutting force and vibration signals captured from dynamometer, microphone and accelerometer were measured. These parameters were then fed to fuzzy system whose output was fed to the developed sensor fusion framework for evaluating tool condition. In [49], tool condition/state was investigated through monitoring AE and vibration signals. AE sensor and accelerometer were placed on cutting tool's shank for monitoring its condition in turning operation. The internal variation was assessed using AE sensor and the external variation was determined using vibration sensor. Experiments depicted that vibration and AE components responded effectively to different turning occurrences and largely influenced the tool state. The vibration elements were found to vary with cutting speed, cutting depth and feed rate. Furthermore, the vibration components' amplitude reduced with enhanced cutting speed while increased with enhanced cutting depth and feed rate. The wear rate progression of tool was determined by AE signal. In [50], TCM in micro-milling procedure was discussed. The parameters influencing tool wear such as AE signals, cutting forces and vibration were examined. A vision mechanism and several sensors were utilized for TCM in milling procedure. Information acquired from accelerometers, AE and force sensors were combined and for recognizing the tool state. The exact tool condition depending on the tool's edge radius was observed without disengaging it from machine. In [51], various TCM methods in milling procedure were discussed. It revealed that selection of suitable features and sensors is important in TCM system's design. Moreover, it highlighted that parameters like vibration, cutting sound, motor current, acoustic emission, torque and cutting force largely influenced TCM in milling processes. Additionally, increased flank wear produced a significant impact on vibration, cutting sound and cutting force. Furthermore, it indicated that utilizing numerous sensors for tool wear monitoring, increased the expenses and enhanced the complexity of acquired signal processing.

Despite numerous benefits offered by multiple sensors in TCM, they are also subject to certain issues. Firstly, utilization of multiple sensors involves high maintenance and production expenses. Moreover, multiple sensors could even lead to deterioration of precision of TCM system owing to interferences created by several sensors and redundant data provided by these sensors. The diverse parameters monitored using distinct sensors is depicted in Table 6.

Table 6:Multiple parameter monitoring

References	Parameters	Workpiece material	Tool used	Monitoring target	HSM operation
[9]	AE signals, cutting force, vibration signals	HRC52 stainless steel	Two-fluted base nose cutter	Diagnosis	Milling
[18]	Spindle current, vibration signals	CG1 450	Face milling cutter	Prognosis	Face milling
[21]	Vibration signals, cutting force	6061-T6 Aluminium alloy	Carbide face mill	Diagnosis	Face milling
[43]	Vibration signals, AE signals, cutting force, spindle power	AISI steel 4340	Two-fluted carbide end mill	Diagnosis	End milling
[44]	AE signals, motor current	Ni steel	Form milling tool	Diagnosis	Form Milling
[45]	Cutting sound, AE signal	Superalloy	Conventional lathe	Diagnosis	Milling
[46]	Power, cutting force, vibration signals	Aluminum blocks	Four-fluted milling cutter	Diagnosis	Milling
[47]	Vibration signals, sound pressure, cutting force, spindle current	C-60 steel	Face-mill cutter	Diagnosis	Face milling

[48]	Cutting sound, cutting force, vibration signals	-	-	Prognosis	Drilling
[49]	AE signals, vibration	Carbon steel	TiN coated carbide	Diagnosis	Turning
[50]	Vibration signals, AE signals, cutting force	Aluminum	Two fluted micro-end mill	Diagnosis	End milling
[53]	Cutting forces, AE signals, torque, vibration signals	Inconel 718	Coromill 360 milling cutter	Prognosis	Milling
[54]	Cutting sound, motor current, cutting force	Steel AISI 1040	TiN coated carbide tools	Diagnosis	Milling
[57]	Vibration signals, AE signals	Titanium alloy	Four-fluted end-mill cutter	Diagnosis	End milling
[63]	Vibration signals, cutting force	Inconel 718	Two-fluted, three-fluted base nose end mill	Diagnosis	End milling

2.2 Feature Extraction

After capturing the sensor signals, they are preprocessed through digital filtering and analog-to-digital conversion for extracting desirable features. Typically, feature extraction is performed for reducing the original information's dimensions and for extracting signal features which are closely linked to tool state. Excessive feature parameters not just enhance the computational burden but even vary the timeliness of TCM process. Additionally, redundant and irrelevant features create an unfavourable impact on TCM performance. Thus, selection of a proper feature extraction approach is essentially important.

In [21], an efficient tool failure detection scheme was proposed. Tests were conducted at distinct tool failure ranges, workpiece mountings, feed rates and spindle speeds. Vibration signals were extracted through Continuous wavelet transform (CWT) method. The approach was effective in detecting tool wear for nonlinear and transient behaviours in HSM process. This approach detected tool failure depending on pattern changes presented on CWT maps by a damaged and healthy tool. However, CWT produced certain redundant data and was computationally slow. In [52], tool wear in face milling operation was detected through cutting sound. Feature extraction schemes like Independent component analysis (ICA) and empirical mode decomposition (EMD) techniques were utilized for separating the worn-out and fresh tool's cutting sound from other tones (sounds). The outcomes were effectively utilized for detecting tool breakage. In [53], several statistical and time domain attributes were extracted from signals for training prediction models for determining cutting tool's state. Utilizing genetic algorithm, only the appropriate features were selected and irrelevant ones were discarded. Feature selection outputs suggested that force-based attributes were useful in sharp tool identification and vibration-based attributes were highly beneficial in tool condition prediction. In [54], sound signals and motor current signals were used as main parameters for monitoring. The motor current parameter was utilized for estimating the force of cutting feed and singular spectrum technique was exploited for extracting tool wear data correlated with sound signal. In [55], various feature extraction schemes like statistical techniques, Discrete Wavelet Transform (DWT) and EMD were compared. Study revealed that DWT exhibited greater accuracy among all the used schemes. In [56], wavelet packet transform technique was employed for decomposing vibration signals. Frequency domain and time domain features in every subband signal were calculated and feature dimensions were reduced through local preserving projection (LPP) method. In [57], DWT approach was utilized for extracting vibration and AE signal's wavelet coefficients. Wavelet attributes were useful in categorizing the tool state. It illustrated that wavelet coefficients obtained from vibration information were more effective in categorizing the tool state than those acquired from AE information.

2.3 Monitoring Models

The signal features extracted through relevant feature extraction methods are fed to monitoring

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models for TCM. Recently, with the terrific advancements in artificial intelligence (AI) domain, numerous AI techniques have been developed. Machine learning (ML), a subset of AI is found to be competent for handling sophisticated mechanical problems like prognostics owing to deterioration procedure and for appropriate decision making and categorization tasks. Hence, ML based decision making approaches have become the popular choice for TCM in HSM operations. The two crucial categories of ML include supervised ML and unsupervised ML. In supervised ML, prediction is done using a labelled dataset whereas in unsupervised ML, prediction is done through identifying patterns of unlabelled datasets. The commonly exploited supervised ML techniques include Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree (DT) and Naive Bayes (NB) and the commonly exploited unsupervised ML techniques include fuzzy clustering (FC) and hidden markov model (HMM). In the present survey, various ML based monitoring models utilized for TCM are explored.

In [54], SVM based TCM was employed. The estimated cutting force and sound signal related information with cutting conditions were fed to least square-SVM (LS-SVM) TCM system for tool state detection. Results illustrated that accuracy of presented TCM system enhanced with high feed rates and cutting speed values. In [56], AI based monitoring models like c-SVM and v-SVM were employed for TCM. For determining wear categories namely new cutter, middle wear, small wear and severe wear, vibration signals equivalent to these tool wear types were collected. The four tool wear types were then distinguished and categorized using v-SVM and c-SVM techniques. Results demonstrated that v-SVM outperformed c-SVM with regard to training time and tool wear categorization. In [57], TCM was achieved using vibration and AE signals with several ML schemes. Tool conditions were predicted using diverse ML schemes. Wavelet attributes were fed as input to ML classifiers like DT, NB, SVM and ANN for categorizing the tool state. Among several ML schemes, SVM performed better in predicting the tool state. In [58], wavelet neural network (NN) approach dependent on computer vision was used for TCM in CNC milling. A diverse range of tests with machining variables of feed rate, machining time, cutting depth and cutting speed were performed. In each test, surface roughness and tool wear were measured. Furthermore, wear images were processed and wear zone descriptor were extracted. Using input variables like feed rate, machining time, cutting depth, cutting speed and wear zone descriptor, the extent of tool wear was predicted. In [59], a methodology for monitoring the face milling equipment was presented. Milling tool's vibration signals were obtained under healthy/normal and faulty conditions for determining the tool state. Furthermore, histogram attributes of obtained signals were extracted and then decision tree method was employed for selecting conspicuous features among extracted ones. K-star technique was used for differentiating and analyzing diverse conditions of tool. Moreover, K-star technique was effective in assessing the tool state with a better response time. In [60], a methodology was presented for TCM online. The extracted vibration signals' statistical features were categorized using K-star technique. In tool condition classification an accuracy of 78% was attained. In [61], HMM was employed for TCM. The research was undertaken for handling sophisticated tool condition switching strategies and several weighting schemes using multi-modal HMM. In [62], Continuous Hidden Markov Model (CHMM) was exploited for TCM and Gaussian regression method was used for predicting the tool's remaining useful lifespan. The CHMM technique detected tool wear state with greater accuracy. In [63], for TCM online and diagnosing faults, several clustering techniques were applied to vibration and force signals of HSM operations. Through applying clustering schemes, the vibration and force signal attributes were examined for determining repeatable and consistent patterns among various cutters in milling. It was witnessed that Fuzzy clustering scheme performed well compared to others. However, fuzzy clustering schemes are employed in only limited studies pertaining to TCM owing to the requirement of numerous clusters for analysis. The various techniques employed for TCM is depicted in Table 7.

Table 7:Multiple parameter monitoring

References	TCM Techniques
[4]	Statistical methods, DWT

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[9]	Multimodal sensing, Wavelet decomposition
[10]	Vibration analysis
[11]	Vibration analysis
[12]	Vibration signal approach
[18]	Multisensor technology
[19]	DWT
[21]	CWT
[22]	Back-propagation NN (BPNN)
[23]	Vibration analysis
[24]	K-star technique, DT
[25]	Fuzzy logic
[27]	Cutting force analysis
[28]	Cutting force analysis
[29]	BPNN
[30]	Probabilistic Neural Network
[32]	Self-organizing map NN
[33]	Wavelet decomposition
[35]	AE technique
[36]	Wavelet transform, ANN
[37]	AE signal analysis
[38]	DT, SVM, ANN
[43]	Multisensor fusion method, SVM, Radial Basis Function, Multilayer Perceptron, Ensemble
[44]	Multisensor fusion approach
[45]	Multisensor data fusion, SVM
[46]	Multi-sensor approach
[47]	Sensor fusion, ANN
[48]	Fuzzy logic, sensor fusion
[49]	Sensor technology
[50]	Multisensor technology, Neuro-fuzzy approach
[52]	ICA, EMD

[53]	Sensor fusion, SVM, Genetic algorithm,
[54]	Linear square-SVM, Singular spectrum
[55]	SVM, DWT, EMD, Statistical methods
[56]	SVM, Nearest neighbor technique, LPP
[57]	DWT, SVM, DT, NB, ANN
[59]	K-star technique, DT
[60]	K-star technique
[61]	HMM
[62]	CHMM, Gaussian regression
[63]	Fuzzy clustering, K-means, K-medoids, Gath-Geva, CWT

3. FPGA-BASED PERFORMANCE MONITORING SYSTEMS

Various FPGA-based performance monitoring systems are developed for diverse monitoring tasks. This section explores the studies on monitoring systems based on FPGA exploited for distinct applications.

In [15], a reconfigurable failure monitoring mechanism based on FPGA for machining operations was discussed. It involved signal filtering and conditioning, data acquisition, data compression, feature extraction and appropriate decision making. The proposed system was simple, cost-effective, reconfigurable, and required no additional processors or personal computers. The entire mechanism was devised using VHDL (VHDL Hardware Description Language) in a FPGA. Current consumption values were monitored for diverse machining operations (hobbing, drilling, turning and milling) without hardware variations for TCM. However, in this work only one channel was utilized for analyzing the current signal from servo drivers. In [64], FPGA-based performance monitoring system was proposed for detecting induction motor failure through vibration analysis. An accelerometer information connected to an induction motor was reviewed for analysis. The proposed FPGA-based performance monitoring system was cost-effective, offered low complexity and reconfigurability and minimum latency. In [65], FPGA-based system was exploited for fault diagnosis and vibration monitoring. It exploited wireless sensor technology for monitoring the machine vibration and diagnosing the fault. Different vibration measurement experiments with unbalanced faults were conducted for validating the sensor node's effectiveness in monitoring machine vibrations. Experimental outputs illustrated that sensor node implementation in FPGA circuit lead to 40% decline in FPGA resource consumption.

In [66], FPGA-based system was employed for monitoring power quality (PQ). PQ variables were determined through signal processing schemes which were applied to voltage and current signals ceaselessly obtained from power network. Furthermore, these processing algorithms were performed as inherent operations in FPGA component and obtained PQ data from measurement locations were forwarded to the server through the communication protocol which was implemented in FPGA. The reporting, storing and monitoring tasks was performed effectively thus providing a beneficial monitoring structure through its innovative hardware and software designs. In [67], FPGA-based system for bearing fault detection was presented. It is intended at addressing the computation complexity in online fault detection tasks. It employed a multicore system with 64 processing elements functioning at 50 MHz frequency in a FPGA for online fault recognition. The FPGA-dependent multicore system executed faster than conventional processors through exploiting the parallelism in fault identification algorithm. Moreover, it outperformed the sequential method running on standard signal processors through significantly lowering the energy utilization. In [68], FPGA based system was proposed for monitoring online PQ perturbations. The PQ perturbations were effectively monitored using proposed FPGA based system with less energy and resource utilization, robust ant-noise behavior, superior categorization accuracy and faster computation. In [69], FPGA-based performance monitoring system was presented for continuously monitoring CNC machinery. In this work, a FPGA-dependent vibration analyzer was developed using fused techniques namely DWT, FFT and FFT-DWT. The devised vibration analyzer was implemented on a FPGA with HSP cores parallely for continuous online and real-time analysis. The proposed FPGA system optimized resources, minimized processing time and outperformed the computer based instruments, reducing the entire costs.

In [70], FPGA based system for monitoring induction motor was discussed. The proposed FPGA based solution provided an intelligent monitoring system which could be integrated with a computer for smart decision making, monitoring the procedure online without disturbing the connected machinery. The approach was efficient in detecting motor defects when fed directly and also when fed using speed drive. In [71], FPGA based system was devised for detecting multiple faults on motors. Information entropy and NNs were employed for identifying several combined faults through analyzing the rotating machine's vibration signals. An FPGA implementation was developed for intelligent online identification of individual and combined defects in real time. This system could precisely detect imbalance, outer-race bearing faults and worn out rotor bars through monitoring vibration signals of the machine continuously. The proposed FPGA-based implementation was cost-effective, consumed less resources and performed real-time monitoring for detecting several defects on induction motors. In [72], FPGA dependent vibration analyzer system was developed for monitoring and identifying machinery failures. The chief goal was to develop an inexpensive 3-axis synchronous vibration analyzer particularly for monitoring embedded machinery to detect mechanical failures. This system detected various mechanical flaws automatically through reconfiguring post-processing method. Moreover, the proposed FPGA-based system could be adopted for detecting other vibration-pertinent mechanical failures owing to its reconfigurable nature. In [73], FPGA based monitoring system was presented for industrial machining applications. The devised system allowed concurrent recording of acoustic pressure, machining forces, noise and accelerations. This system was useful for selecting, obtaining and processing machining signals efficiently.

The promising outcomes obtained from FPGA-based performance monitoring systems in afore-discussed studies in monitoring diverse applications have motivated the implementation of FPGA-based systems for TCM.

4. ROLE OF FPGA IN TOOL CONDITION MONITORING

Flexible machining and reconfigurability is becoming a vital requisite for current manufacturing systems. The devised systems should be reconfigurable and flexible for complex and diverse processes encountered in machining applications. The extracted signal features may have dissimilar properties for these processes and thus signal processing potential of such systems requires a superior level of scalability and the capacity to process the growing volume of information in a controllable time limit. Such a notable technology which has mellowed over the past years is the FPGA. FPGAs are basically integrated circuits (ICs) which can be reconfigured for performing tasks which normally were performed through application specific ICs (ASICs). Recently, FPGA technology is extensively applied in monitoring machining processes wherein a system-on-chip (SoC) is developed for acquiring and processing several vibration signals helpful in TCM. FPGA-based systems are eminent and extremely valuable in TCM. These systems employ VHDL language and facilitate real-time and online monitoring because of parallel processing and robust processing speed of FPGA. Digital filter with FPGA results in compact implementation as both support and control components are equipped within the same chip. FPGA enables development of flexible digital structures that are easily adaptable to various machining conditions without requiring any hardware alteration. Moreover, these systems reduce the expenses compared to software or analog TCM systems. They maintain lower costs as system installation does not need any tool-structure modification.

4.1 FPGA based systems for TCM

In [74], a FPGA-dependent reconfigurable system for real-time and online TCM in HSM process was presented. The proposed FPGA system comprised a hardware signal processing (HSP) and data acquisition (DA) unit. The generated vibration signals from machining procedures conducted using cutting parameters and distinct tool conditions were acquired and digitalized using the DA system. The digitalized signals were processed by HSP unit through reconfigurable digital filter. The proposed TCM system operated in two diverse modes namely learning mode (LM) and monitoring mode (MM). In the LM, data essential for TCM was acquired and processed for setting a healthy or normal-tool threshold. In the MM, the system acquired, filtered and estimated the average value and compared the information with the threshold set in LM for indicating and detecting the tool state during HSM operation. The employed digital filter allowed extraction of data from frequency band which displayed dominant frequencies on occurrence of tool failures. The threshold and frequency band were configured and adjusted according to cutting variables set during HSM procedure. Tool condition was indicated using a LED indicator, alarm signal and the message displayed on a seven-segment display. Results demonstrated a 100% tool condition indication and detection. Moreover, this system eliminated tool modification and prevented interference with cutting operation.

In [75], FPGA-dependent combined smart-sensor was developed for quantitative measurement of tool-wear region in machine inserts. The chief motive was to enhance the online measurement of wear region in the machine through the data provided by the accelerometer and servoamplifier. The flank-wear region estimation errors were diminished through a weighting function depending on the output of vibration and current signals besides the machining variables. This work demonstrated that fusion of vibration and current signals helped in attaining better accuracy than when vibration and current signals, used separately. In [76], FPGA based performance monitoring system for TCM in intelligent CNC machines was proposed. It employed a sensorless mechanism for measuring cutting force. A DWT function was utilized for estimating tool breakage in machines. The HSP unit implemented on a FPGA performed the intensive computations. Moreover, HSP unit allowed effective on-line detection of tool breakage within 38.9 µs. This system achieved substantial cost reduction due to the utilization of application specific HSP as a one-chip solution containing the detection method and its realization on FPGA. The proposed FPGA system was an autonomous unit and it eliminated computers or microprocessors for performing its task. In [77], an approach for TCM in a sophisticated grinding operation using FPGA was discussed. It demonstrated how multisensory multiple-processing approach could be realized and devised for high-level condition monitoring in industrial machining operations. The approach was illustrated as an operating solution for position and state oriented condition monitoring of grinding process. In [78], FPGA based TCM system was presented for monitoring the induction motor's condition. For diagnosing, identifying and forecasting faults, three automated methods implemented on FPGA were used. The NN technique was utilized for estimating the occurrence of instantaneous changes. Fuzzy logic technique was employed for detecting stator condition. Negative selection method was utilized for detecting defective rotor bar flaws. These methods were operated synchronously on FPGA. Validation of system's performance indicated the efficacy and accuracy in determining motor condition. Moreover, the proposed FPGA based implementation facilitated real-time operation with 2 milliseconds of processing time. It guaranteed a cost-effective solution owing to concurrent or parallel processing potential of FPGA. Results indicated that proposed FPGA system was effective in monitoring the occurred faults in motors.

Recently, TCM systems based on python programming have been implemented. In [79], machine tool monitoring systems were developed. These systems collected information from several CNC machine tools which relied on MTConnect protocol, Python and cloud system for monitoring. In [80], a model for TCM based on python implementation was devised. The experimental setup involved two DC motor sets and a device for monitoring and suitable decision making. A vibration analytic component was employed for streaming and acquisition of vibration signals. The shaft vibration of DC motor was acquired through vibration sensors and data was communicated to cloud using python application. Every machine's vibration thresholds were estimated for monitoring their condition. These thresholds conforming to different environmental and operating conditions were maintained in cloud for TCM and improving maintenance decisions. In [81], an approach for monitoring CNC machine tools was presented. The implementation was done using python programming. It focussed on processing and collecting operational information using simpler and cheaper components. The devised system's feasibility was evaluated by testing a prototype with 3-axis CNC machine (milling machine). The outcomes revealed that the presented monitoring system decreased the time and complexity for use and installation. Additionally, it offered easy integration, reduced expenses and change of tools. Moreover, the proposed notion showed a feasibility for any digitally controlled equipment having a suitable display for operators (human operators). In [82], machine condition monitoring (MCM) was discussed. It emphasized on sparse coding technique for compression of signal for MCM. The technique's feasibility was evaluated through vibration signals arriving from spindle part of machines. Signal compressions were implemented in python language. The sparse coding technique offered better vibration compression than classical techniques of DWT and DCT.

The majority of the described TCM systems are built for rigid cutting parameters. However, in the real world, machining processes are carried out under a wide range of cutting conditions. As a result, the TCM system's ability to quickly and easily adjust to new settings for a variety of cutting variables is an important feature that should be taken into account during the design process. Incompatibile analysis methods and slower processing times are used by some systems. If these unsuitable approaches are used for system analysis, it is possible that vital TCM system enhancements, and therefore their output performance, would be compromised.

5. CONCLUSION

TCM is an essential action in HSM procedures. It is a critical problem in machining for product quality control as the anomalous tool conditions and excessive tool breakage would substantially shorten or reduce the tool's durability. Online TCM systems are largely essential in present manufacturing sectors for growing demands of cost minimization and quality enhancement. This paper discussed the necessity of TCM in machining procedures. The paper reviewed numerous TCM systems, parameters employed for monitoring tool's state and techniques exploited for TCM. It elucidated the prominence of FPGA-based performance monitoring systems in TCM. It reviewed numerous FPGA-based performance monitoring systems devised for distinct applications. It explained the important role played by these systems in TCM. Numerous conventional TCM systems (without FPGA) employed in existing works are inflexible, not reconfigurable and not suitable to monitor tool states in diverse machining tasks simultaneously. Moreover, majority of existing TCM systems are devised to operate only in single machining procedure. Therefore, these systems are highly inefficient for TCM during different HSM operations. However, with the use of FPGA-based performance monitoring systems, the problems experienced in conventional TCM systems are reduced widely owing to their scalability, reconfigurability and ability to monitor tool states in numerous machining processes simultaneously. FPGA-based performance monitoring systems are highly adaptable to distinct machining conditions without requiring any hardware alteration. Moreover, these systems are inexpensible compared to software or analog TCM systems and involve lower system installation costs. Additionally, real-time and online tool state monitoring could be achievable because of their parallel processing and robust processing speed, thus making them very efficient and useful for TCM in HSM operations. In future, hybrid approaches can be used for better performance.

REFERENCES:

[1] Ahmad, M. I., Yusof, Y., Daud, M. E., Latiff, K., Kadir, A. Z. A., & Saif, Y. (2020). Machine monitoring system: a decade in review. *The International Journal of Advanced Manufacturing Technology*, 1-15.

[2] Akin, E., Aydin, I., & Karakose, M. (2011, March). FPGA based intelligent condition monitoring of induction motors: Detection, diagnosis, and prognosis. In 2011 IEEE International Conference on Industrial Technology (pp. 373-378). IEEE.

[3] Aliustaoglu, C., Ertunc, H. M., & Ocak, H. (2009). Tool wear condition monitoring using a sensor fusion model based on fuzzy inference system. *Mechanical Systems and Signal Processing*, *23*(2), 539-546.

[4] Ambhore, N., Kamble, D., Chinchanikar, S., & Wayal, V. (2015). Tool condition monitoring system: A review. *Materials Today: Proceedings*, *2*(4-5), 3419-3428.

[5] Arun, A., Rameshkumar, K., Unnikrishnan, D., & Sumesh, A. (2018). Tool condition monitoring of cylindrical grinding process using acoustic emission sensor. *Materials Today: Proceedings*, *5*(5), 11888-11899.
[6] Azmi, A. I. (2015). Monitoring of tool wear using measured machining forces and neuro-fuzzy modelling approaches during machining of GFRP composites. *Advances in Engineering Software*, *82*, 53-64.
[7] Bengherbia, B., Zmirli, M. O., Toubal, A., & Guessoum, A. (2017). FPGA-based wireless sensor nodes for vibration monitoring system and fault diagnosis. *Measurement*, *101*, 81-92.
[8] Bhuiyan, M. S. H., Choudhury, I. A., & Nukman, Y. (2012, July). Tool condition monitoring using acoustic emission and vibration signature in turning. In *Proceedings of the world congress on engineering* (Vol. 3, pp. 1-5).
[9] Cabal-Yepez, E., Valtierra-Rodriguez, M., Romero-Troncoso, R. J., Garcia-Perez, A., Osornio-Rios, R. A., Miranda-Vidales, H., & Alvarez-Salas, R. (2012). FPGA-based entropy neural processor for online detection of multiple combined faults on induction motors. *Mechanical Systems and Signal Processing*, *30*, 123-130.
[10] Cho, S., Binsaeid, S., & Asfour, S. (2010). Design of multisensor fusion-based tool condition monitoring system in end milling. *The International Journal of Advanced Manufacturing Technology*, *46*(5-8), 681-694.
[11] Contreras-Medina, L. M., Romero-Troncoso, R. J., Millan-Almaraz, J. R., & Rodriguez-Donate, C. (2008, June). FPGA based multiple-channel vibration analyzer embedded system for industrial applications in automatic failure detection. In 2008 International Symposium on Industrial Embedded Systems (pp. 229-232). IEEE.
[12] Cuka, B., & Kim, D. W. (2017). Fuzzy logic based tool condition monitoring for end-milling. *Robotics and Computer-Integrated Manufacturing*, *47*(C), 22-36.
[13] de Jesus Rangel-Magdaleno, J., de Jesus Romero-Troncoso, R., Osornio-Rios, R. A., Cabal-Yepez, E., & Dominguez-Gonzalez, A. (2010). FPGA-based vibration analyzer for continuous CNC machinery monitoring with fused FFT-DWT signal processing. *IEEE Transactions on Instrumentation and Measurement*, *59*(12), 3184-3194.
[14] de Jesús, R. T. R., Gilberto, H. R., Iván, T. V., & Carlos, J. C. J. (2004). FPGA based on-line tool breakage detection system for CNC milling machines. *Mechatronics*, *14*(4), 439-454.
[15] Deng, C., Guo, R., Zheng, P., Liu, C., Xu, X., & Zhong, R. Y. (2018). From open CNC systems to cyber-physical machine tools: a case study. *Procedia CIRP*, *72*, 1270-1276.
[16] Dimla, D. E. (2002). The correlation of vibration signal features to cutting tool wear in a metal turning operation. *The International Journal of Advanced Manufacturing Technology*, *19*(10), 705-713.
[17] Franco-Gasca, L. A., de Jesús Romero-Troncoso, R., Herrera-Ruiz, G., & del Rocío Peniche-Vera, R. (2009). FPGA based failure monitoring system for machining processes. *The International Journal of Advanced Manufacturing Technology*, *40*(7-8), 676-686.
[18] Ganga, D., & Ramachandran, V. (2018). IoT-based vibration analytics of electrical machines. *IEEE Internet of Things Journal*, *5*(6), 4538-4549.
[19] Geramifard, O., Xu, J. X., Zhou, J. H., & Li, X. (2013). Multimodal hidden Markov model-based approach for tool wear monitoring. *IEEE Transactions on Industrial Electronics*, *61*(6), 2900-2911.
[20] Ghosh, N., Ravi, Y. B., Patra, A., Mukhopadhyay, S., Paul, S., Mohanty, A. R., & Chattopadhyay, A. B. (2007). Estimation of tool wear during CNC milling using neural network-based sensor fusion. *Mechanical Systems and Signal Processing*, *21*(1), 466-479.
[21] Giriraj, B., Raja, V. P., Gandhinadhan, R., & Ganeshkumar, R. (2006). Prediction of tool wear in high speed machining using acoustic emission technique and neural network.
[22] Goh, W. L., & Sadjoli, N. (2018). Feasibility of dictionary-based sparse coding for data compression in machine condition-based monitoring. In *2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS)* (pp. 1-6). IEEE.
[23] Gómez, M. P., Hey, A. M., Ruzzante, J. E., & D'Attellis, C. E. (2010). Tool wear evaluation in drilling by acoustic emission. *Physics Procedia*, *3*(1), 819-825.
[24] Haber, R. E., Jiménez, J. E., Peres, C. R., & Alique, J. R. (2004). An investigation of tool-wear monitoring in a high-speed machining process. *Sensors and Actuators A: Physical*, *116*(3), 539-545.
[25] Hsieh, W. H., Lu, M. C., & Chiou, S. J. (2012). Application of backpropagation neural network for spindle vibration-based tool wear

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monitoring in micro-milling. *The International Journal of Advanced Manufacturing Technology*, *61*(1-4), 53-61.

[26]Huang, P. B., Ma, C. C., & Kuo, C. H. (2015). A PNN self-learning tool breakage detection system in end milling operations. *Applied Soft Computing*, *37*, 114-124.

[27]Humphreys, I., Eisenblätter, G., & O'Donnell, G. E. (2014). FPGA based monitoring platform for condition monitoring in cylindrical grinding. *Procedia CIRP*, *14*, 448-453.

[28]Kang, M., Kim, J., & Kim, J. M. (2014). An FPGA-based multicore system for real-time bearing fault diagnosis using ultrasampling rate AE signals. *IEEE Transactions on Industrial Electronics*, *62*(4), 2319-2329.

[29]Kaya, B., Oysu, C., Ertunc, H. M., & Ocak, H. (2012). A support vector machine-based online tool condition monitoring for milling using sensor fusion and a genetic algorithm. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *226*(11), 1808-1818.

[30]Kim, H., Jung, W. K., Choi, I. G., & Ahn, S. H. (2019). A Low-Cost Vision-Based Monitoring of Computer Numerical Control (CNC) Machine Tools for Small and Medium-Sized Enterprises (SMEs). *Sensors*, *19*(20), 4506.

[31]Krishnakumar, P., Rameshkumar, K., & Ramachandran, K. I. (2018). Machine learning based tool condition classification using acoustic emission and vibration data in high speed milling process using wavelet features. *Intelligent Decision Technologies*, *12*(2), 265-282.

[32]Lee, B. Y. (1999). Application of the discrete wavelet transform to the monitoring of tool failure in end milling using the spindle motor current. *The International Journal of Advanced Manufacturing Technology*, *15*(4), 238-243.

[33]Lin, S. C., & Ting, C. J. (1996). Drill wear monitoring using neural networks. *International Journal of Machine Tools and Manufacture*, *36*(4), 465-475.

[34]Lynn, R., Louhichi, W., Parto, M., Wescoat, E., & Kurfess, T. (2017, June). Rapidly deployable MTConnect-based machine tool monitoring systems. In *International Manufacturing Science and Engineering Conference* (Vol. 50749, p. V003T04A046). American Society of Mechanical Engineers.

[35]Madhusudana, C. K., Kumar, H., & Narendranath, S. (2016). Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal. *Engineering science and technology, an international journal*, *19*(3), 1543-1551.

[36]Madhusudana, C. K., Kumar, H., & Narendranath, S. (2016). Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal. *Engineering science and technology, an international journal*, *19*(3), 1543-1551.

[37]Madhusudana, C. K., Kumar, H., & Narendranath, S. (2017). Face milling tool condition monitoring using sound signal. *International Journal of System Assurance Engineering and Management*, *8*(2), 1643-1653.

[38]Malekian, M., Park, S. S., & Jun, M. B. (2009). Tool wear monitoring of micro-milling operations. *Journal of Materials Processing Technology*, *209*(10), 4903-4914.

[39]Millan-Almaraz, J. R., Romero-Troncoso, R. J., Contreras-Medina, L. M., & Garcia-Perez, A. (2008, June). Embedded FPGA based induction motor monitoring system with speed drive fed using multiple wavelet analysis. In *2008 International Symposium on Industrial Embedded Systems* (pp. 215-220). IEEE.

[40]Mohanraj, T., Shankar, S., Rajasekar, R., Sakthivel, N. R., & Pramanik, A. (2020). Tool condition monitoring techniques in milling process—A review. *Journal of Materials Research and Technology*, *9*(1), 1032-1042.

[41]Nouri, M., Fussell, B. K., Ziniti, B. L., & Linder, E. (2015). Real-time tool wear monitoring in milling using a cutting condition independent method. *International Journal of Machine Tools and Manufacture*, *89*, 1-13.

[42]Ong, P., Lee, W. K., & Lau, R. J. H. (2019). Tool condition monitoring in CNC end milling using wavelet neural network based on machine vision. *The International Journal of Advanced Manufacturing Technology*, *104*(1-4), 1369-1379.

[43]Orhan, S., Er, A. O., Camuşcu, N., & Aslan, E. (2007). Tool wear evaluation by vibration analysis during end milling of AISI D3 cold work tool steel with 35 HRC hardness. *NDT & E International*, *40*(2), 121-126.

[44]Painuli, S., Elangovan, M., & Sugumaran, V. (2014). Tool condition monitoring using K-star algorithm. *Expert Systems with Applications*, *41*(6), 2638-2643.

[45]Patra, K. (2011, July). Acoustic emission based tool condition monitoring system in drilling. In *Proceedings of the world congress on engineering* (Vol. 3, pp. 6-8).

[46]Pechenin, V. A., Khaimovich, A. I., Kondratiev, A. I., & Bolotov, M. A. (2017). Method of controlling cutting tool wear based on signal analysis of acoustic emission for milling. *Procedia Engineering*, *176*, 246-252.

[47]Prickett, P. W., & Johns, C. (1999). An overview of approaches to end milling tool monitoring. *International Journal of Machine Tools and Manufacture*, *39*(1), 105-122.

[48]Randall, R. B. (2011). *Vibration-based condition monitoring: industrial, aerospace and automotive applications*. John Wiley & Sons.

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

[50]Rivero, A. D., de Lacalle, L. L., & Penalva, M. L. (2008). Tool wear detection in dry high-speed milling based upon the analysis of machine internal signals. *Mechatronics*, *18*(10), 627-633.

[51]Sahani, M., & Dash, P. K. (2019). FPGA-based online power quality disturbances monitoring using reduced-sample HHT and class-specific weighted RVFLN. *IEEE Transactions on Industrial Informatics*, *15*(8), 4614-4623.

[52]Salgado, D. R., & Alonso, F. J. (2007). An approach based on current and sound signals for in-process tool wear monitoring. *International Journal of Machine Tools and Manufacture*, *47*(14), 2140-2152.

[53]Sevilla, P. Y., Jauregui, J. C., Herrera, G., & Robles, J. B. (2013). Efficient method for detecting tool failures in high-speed machining process. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *227*(4), 473-482.

[54]Sevilla-Camacho, P. Y., Herrera-Ruiz, G., Robles-Ocampo, J. B., & Jáuregui-Correa, J. C. (2011). Tool breakage detection in CNC high-speed milling based in feed-motor current signals. *The International Journal of Advanced Manufacturing Technology*, *53*(9-12), 1141-1148.

[55]Sevilla-Camacho, P. Y., Robles-Ocampo, J. B., Jauregui-Correa, J. C., & Jimenez-Villalobos, D. (2015). FPGA-based reconfigurable system for tool condition monitoring in high-speed machining process. *Measurement*, *64*, 81-88.

[56]Sevilla-Camacho, P. Y., Robles-Ocampo, J. B., Muñiz-Soria, J., & Lee-Orantes, F. (2015). Tool failure detection method for high-speed milling using vibration signal and reconfigurable bandpass digital filtering. *The International Journal of Advanced Manufacturing Technology*, *81*(5), 1187-1194.

[57]Shao, H., Wang, H. L., & Zhao, X. M. (2004). A cutting power model for tool wear monitoring in milling. *International Journal of Machine Tools and Manufacture*, *44*(14), 1503-1509.

[58]Shi, X., Wang, R., Chen, Q., & Shao, H. (2015). Cutting sound signal processing for tool breakage detection in face milling based on empirical mode decomposition and independent component analysis. *Journal of Vibration and Control*, *21*(16), 3348-3358.

[59]Shome, S. K., Datta, U., & Vadali, S. R. K. (2012). FPGA based signal prefiltering system for vibration analysis of induction motor failure detection. *Procedia Technology*, *4*, 442-448.

[60]Sivasakthivel, P. S., & Sudhakaran, R. (2013). Optimization of machining parameters on temperature rise in end milling of Al 6063 using response surface methodology and genetic algorithm. *The International Journal of Advanced Manufacturing Technology*, *67*(9-12), 2313-2323.

[61]Stavropoulos, P., Papacharalampopoulos, A., Vasiliadis, E., & Chryssolouris, G. (2016). Tool wear predictability estimation in milling based on multi-sensorial data. *The International Journal of Advanced Manufacturing Technology*, *82*(1-4), 509-521.

[62]Sundaram, S., Senthilkumar, P., Kumaravel, A., & Manoharan, N. (2008). Study of flank wear in single point cutting tool using acoustic emission sensor techniques. ARPN Journal of Engineering and Applied Sciences, 3(4), 32-36.

[63]Tansel, I. N., Arkan, T. T., Bao, W. Y., Mahendrakar, N., Shisler, B., Smith, D., & McCool, M. (2000). Tool wear estimation in micro-machining.: Part I: tool usage–cutting force relationship. *International Journal of Machine Tools and Manufacture*, *40*(4), 599-608.

[64]Torabi, A. J., Er, M. J., Li, X., Lim, B. S., & Peen, G. O. (2015). Application of clustering methods for online tool condition monitoring and fault diagnosis in high-speed milling processes. *IEEE Systems Journal*, *10*(2), 721-732.

[65]Trejo-Hernandez, M., Osornio-Rios, R. A., Romero-Troncoso, R. D. J., Rodriguez-Donate, C., Dominguez-Gonzalez, A., & Herrera-Ruiz, G. (2010). FPGA-based fused smart-sensor for tool-wear area quantitative estimation in CNC machine inserts. *Sensors*, *10*(4), 3373-3388.

[66]Uekita, M., & Takaya, Y. (2017). Tool condition monitoring for form milling of large parts by combining spindle motor current and acoustic emission signals. *The International Journal of Advanced Manufacturing Technology*, *89*(1-4), 65-75.

[67]Urbikain, G., & de Lacalle, L. L. (2020). Monithor: a complete monitoring tool for machining data acquisition based on fpga programming. *SoftwareX*, *11*, 100387.

[68]Wang, G. F., Yang, Y. W., Zhang, Y. C., & Xie, Q. L. (2014). Vibration sensor based tool condition monitoring using ν support vector machine and locality preserving projection. *Sensors and Actuators A: Physical*, *209*, 24-32.

[69]Wang, M., & Wang, J. (2012). CHMM for tool condition monitoring and remaining useful life prediction. *The International Journal of Advanced Manufacturing Technology*, *59*(5), 463-471.

[70]Yen, C. L., Lu, M. C., & Chen, J. L. (2013). Applying the self-organization feature map (SOM) algorithm to AE-based tool wear monitoring in micro-cutting. *Mechanical Systems and Signal Processing*, *34*(1-2), 353-366.

[71]Yesilyurt, I., & Ozturk, H. (2007). Tool condition monitoring in milling using vibration analysis. *International journal of production research*, *45*(4), 1013-1028.

[72]Yildirim, O., Eristi, B., Eristi, H., Unal, S., Erol, Y., & Demir, Y. (2018). FPGA-based online power quality monitoring system for electrical distribution network. *Measurement*, *121*, 109-121.

[73]Zeng, H., Thoe, T. B., Li, X., & Zhou, J. (2006, August). Multi-modal sensing for machine health monitoring in high speed machining. In *2006 4th IEEE International Conference on Industrial Informatics* (pp. 1217-1222). IEEE.

[74]Zhang, H., Zhao, J., Wang, F., Zhao, J., & Li, A. (2015). Cutting forces and tool failure in high-speed milling of titanium alloy TC21 with coated carbide tools. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *229*(1), 20-27.

[75]Zhang, J. Z., & Chen, J. C. (2008). Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system. *The International Journal of Advanced Manufacturing Technology*, *39*(1-2), 118-128.

[76]Zhang, J. Z., & Chen, J. C. (2008). Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system. *The International Journal of Advanced Manufacturing Technology*, *39*(1-2), 118-128.

[77]Zhang, K. F., Yuan, H. Q., & Nie, P. (2015). A method for tool condition monitoring based on sensor fusion. *Journal of Intelligent Manufacturing*, *26*(5), 1011-1026.

[78]Zhang, S, J.F. Li, J. Sun, F. Jiang, (2010). Tool wear and cutting forces vibration in high speed end-milling of Ti-6Al-4V alloy. Int. J. Adv. Manuf. Technol., 46, 69-78.

[79]Zhang, X. Y., Lu, X., Wang, S., Wang, W., & Li, W. D. (2018). A multi-sensor based online tool condition monitoring system for milling process. *Procedia CIRP*, *72*, 1136-1141.

[80]Zhong, R. Y., Wang, L., & Xu, X. (2017). An IoT-enabled real-time machine status monitoring approach for cloud manufacturing. *Procedia CIRP*, *63*, 709-714.

[81]Zhu, K., & Vogel-Heuser, B. (2014). Sparse representation and its applications in micro-milling condition monitoring: noise separation and tool condition monitoring. *The International Journal of Advanced Manufacturing Technology*, *70*(1-4), 185-199.

[82] Zhu, K., San Wong, Y., & Hong, G. S. (2009). Wavelet analysis of sensor signals for tool condition monitoring: A review and some new results. *International Journal of Machine Tools and Manufacture*, *49*(7-8), 537-553