Sustainable Production, Instrumentation and Engineering Sciences *No. 1| 2023*
https://doi.org/10.57223/spies.2023.1.1.05

Havva Demirpolat[1], Mustafa Kuntoğlu[1], Rüstem Binali[1]
[1]Selcuk University, Technology Faculty, Mechanical Engineering Department,
Konya, 42130, Turkey, hdemirpolat@selcuk.edu.tr;https://orcid.org/0000-0002-2981-9867
[1]Selcuk University, Technology Faculty, Mechanical Engineering Department,
Konya, 42130, Turkey, mkuntoglu@selcuk.edu.tr;https://orcid.org/0000-0002-7291-9468
[1]Selcuk University, Technology Faculty, Mechanical Engineering Department,
Konya, 42130, Turkey, rustem.binali@selcuk.edu.tr;https://orcid.org/0000-0003-0775-3817

A review on machinability in the milling processes

KEYWORDS

milling process, cutting force, surface roughness, tool wear.

ABSTRACT

This review paper focuses on the up-to-date machinability characteristics of milling processes such as cutting forces, surface roughness and tool wear and their impacts on the cutting mechanism. The methodology pursued in this paper is to analyze the previous research articles published between 2019–2022 classifying them into the subcategories that use milling operation as manufacturing strategy. As known, milling is one of the most used machining processes in industry and often applied for academic studies for a wide range of materials. Therefore, used sensor systems, main aim and the preferred methodology were summarized in the context of this paper. Seemingly, a great number of machinability papers have been published recently which focuses on the several types of engineering materials and utilized various types of sensor system to improve the surface roughness and tool life. In addition, the investigation showed that optimization approaches have been applied broadly to detect the best machining conditions. Also, it was observed that several modeling approaches such as finite element analysis is a good alternative to analyze the process.

Introduction

Machining is the most popular manufacturing method in the industry. Milling is a widely used method in machining operations. Other primary methods can be sorted as turning, drilling, and grinding. Milling is the process of removing chips from the material of the cutting tool with the movement of the workpiece material along the coordinate planes at each turn of the cutting tool. The cutting tool used in this process is not single edged as in the turning process, but multi-edged. For this reason, the cutting mechanics are different from the other machining operations, and it is important to investigate the milling process by researchers. Therefore, machinability tests, which remain popular, are carried out to understand the mechanics of cutting and to ensure that the materials are produced as desired. The main purpose of performing these tests is due to the undesired changes due to the interaction of the cutting tool and workpiece material with each other during machining. These changes are factors such as tool wear, temperature, cutting force and surface roughness. The machining parameters used during the process (cutting speed, feed rate, depth of cut and cutting conditions etc.) constitute the criteria of machinability tests. In these criteria, output parameters such as temperature, force, wear, and roughness occur during the process. With the interaction of the input and output parameters, it is ensured that the product with the desired quality and efficiency is obtained. Therefore, machinability tests are very important in the industry.Some of the typical machinability properties of milling processes include:

- ✓ The surface roughness that depends on factors such as the tool geometry, cutting speed, feed rate, and depth of cut.
- ✓ Chip formation: the type and shape of chips produced during milling can affect the surface finish and tool wear. Long, continuous chips are desirable, while short, broken chips can cause tool wear and surface roughness.
- ✓ Tool wear: the cutting tool can experience different types of wear during milling, including flank wear, crater wear, and chipping. The rate and type of wear depend on factors such as the tool material, coating, cutting speed, feed rate, and cutting depth.
- ✓ Material removal rate: the material removal rate (MRR) is the volume of material removed per unit time. The MRR depends on factors such as the cutting speed, feed rate, depth of cut, and workpiece material properties.
- ✓ Power consumption: the power consumption during milling depends on the cutting parameters, tool geometry and material, and workpiece material properties. High power consumption can indicate excessive tool wear or an inefficient cutting process.
- ✓ Surface integrity: the milling process can affect the surface integrity of the workpiece, including residual stresses, surface hardening, and microstructural changes. The surface integrity depends on factors such as the cutting parameters, workpiece material properties, and cooling and lubrication methods used.

The creation of a convenient and ideal machining system in machining brings reliable operation. One of the most important output parameters is tool wear, which is included in many studies in the literature. The reason for this is that the output parameters are adversely affected due to the machining parameters that affect the tool wear. That is, tool wear is affected by cutting speed, feed rate, tool wear resistance, vibration, temperature, poor unmachined surface quality and high cutting forces during the process. Thus, there is a continuous change in the dimensions of the workpiece, resulting in an increase in the number of wasted parts. To prevent these negative situations, it is necessary to determine the amount of wear by measuring methods. If there are faulty values in line with the measured values, the required parameters and processing conditions are changed to minimize the wear and the part size is brought to the desired size and quality.

Another important criterion in machinability tests is surface roughness [1, 2]. Tool wear is the most important factor affecting the deterioration of the machined surface of the workpiece material. As a result of the defective surface and part, it will not be produced within the quality tolerances and will cause the geometric tolerances to change. For example, due to tool wear after the finishing process of a prismatic part, there will be differences in the thickness of the part as well as the roughness differences between the starting and ending surfaces of the part [3, 4]. As a result of the process, linearity will be deteriorated and a curved surface will be obtained. In addition, depending on the increased wear amount, the cutting force required to remove chips also increases and causes the tool to break [5]. The resistances that occur during chip removal are overcome by cutting forces. Cutting forces cause some deformations on both the tool and the workpiece, and they change the tool-workpiece position and affect both the surface quality and the tool. The cutting part-tool-machine chain is a flexible system. Therefore, during chip removal, vibrations may occur due to the variable cutting force. When these vibrations are severe, they also create chatter, which causes poor surface quality [6]. Figure 1 represents the concept of the article.

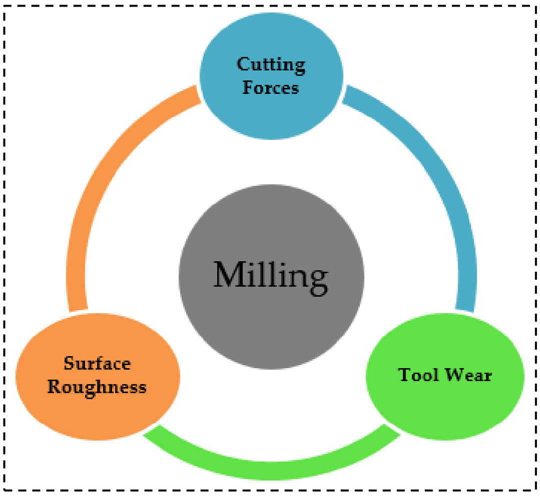

Fig. 1. The concept of the article

We hope the presented approach will be useful as a guide for people in both the academic community and industry researching machinability criteria in milling operations. The aim of the study is to determine the effects of preferred machinability input parameters on cutting forces, surface roughness and tool wear in machinability studies performed by milling method. For this reason, the study is discussed on cutting force, surface roughness and tool wear.

The effect of cutting forces in milling

In order to carry out efficient operations in the milling method, cutting forces must be determined and the cutting tools and workpieces must be selected and dimensioned properly. Therefore, it is necessary to investigate the cutting force in detail. The thickness of the chip formed during the process varies throughout the cutting cycle, resulting in variable cutting forces and contact conditions. In addition, fluctuations occur in cutting forces due to the cutting of more than one cutting edge in milling. The cutting forces in milling vary according to many factors such as the type of milling, the position of the cutting tool, the workpiece material, the geometry of the cutting tool, the thickness of the chip formed during the process, the type of wear on the cutting tool and the machining parameters. Below the literature review of machinability studies made by milling is presented.

Milling process researches are important to determine the environmental conditions and cutting parameters. The voxel based prediction analysis results were compared with the experimental results with regard to cutting force [7]. Discretized voxel method that accepted relatively basic prediction methods were convenient with experimental study an literature. Generally milling force is predicted from orthogonal cutting data [8]. But machine tool systems' dynamic conditions have serious effects on its prediction accuracy. A new data-driven prediction method has been suggested that requires few tests by authors. A sufficient cutting data has been obtained with the effect of dynamic properties thanks to a correction coefficient by the cutting forces orthogonal helical milling transformation. Predicting milling force is important to improve the tool life and to guarantee machining quality[9]. Much research has been conducted to predict a credible cutting force [10]. proposed a new approach for estimating the cutting force coefficient. Machining experiments were conducted with different tools to compare each other for instantaneous cutting force prediction. Thus, they showed that highly accurate estimation can be obtained for the variable workpiece and tools. An algorithm was designed to predict the cutting force truly for variable tool guidance with the Cutter Workpiece Engagement (CWE) challenging [11] [12]. It was established as a geometric analytical method to predict the milling process with a cutting force model. Bernini et al. have revealed that the micro-milling process with material separation model could be validated for cutting force. An online estimation of specific force coefficient (SFC) is proposed [13]. The principal Component Regression model accepted the five different cutting speeds on two different machine tools to estimate the variable of coefficients modeled a predicting cutting force method milling process. Euler-Bernoulli beam theory has been used to calculate the deformation of a workpiece at any cutting depth [14]. A new method to determine both radial and axial depth of circumferential end milling process using cutting force signal has been developed by [15]. The literature survey is summarized in Table 1.

Table 1. Literature review of cutting force studies

Type of sensors	Machine	Process	Workpiece	Output parameters	Aim	Ref.
Dynamometer	CNC vertical machine	Milling	EN AW 6061	Voxel sizes variation, number of flutes	A comparison between experiments with different types of end mill tools and predicted force	[7]
Dynamometer	CNC vertical machine	Milling	Ti6Al4V	Cutting force coefficients, cutting force correction factor	To Predict Milling force with Transfer learning methods	[8]
Dynamometer	CNC vertical machine	Milling	Ti6Al4V	Machine tool correction coefficient, cutting force predictions	A new cutting force prediction model consist of with ortogonal and experimental data.	[16]
Dynamometer, power meter	3-axis vertical machine	Milling	Ti6Al4V	Cutting parameters and measured power	The indirect evaluation method has been applied to determine the cutting force coefficient.	[10]
Dynamometer	5-axis CNC vertical machine	Milling	EN AW 7075	Milling force coefficient	Modeling the cutting force under different machining conditions.	[11]
–	ABAQUS	Milling	Al7050-T7451 Ti6Al4V	FEM model cutting force coefficients	An analytical material separation model was suggested to predicting the cutting force for different workpiece.	[12]
Dynamometer, microscope	5-axis CNC vertical machine	Milling	Ti_6Al_4V	Cutting force coefficient	To estimate the Specific force coefficient (SCF) in high-feed milling condition and monitoring tool condition.	[13]
Dynamometer	5-axis CNC	Milling	6061-Tb51	Measured cutting force, predicted cutting force	High accuracy prediction on cutting force by material constitutive model-based.	[14]
Dynamometer	Milling machine	Milling	EN AW 6082-T4	Cutting force signals	A force based peripheral milling models without cutting force coefficient.	[15]

The effect of tool wear in milling

Tool wear can be expressed as the loss of material in the cutting tool during the formation of a new surface and chip formation in machining. Material loss is usually slow, but can occasionally be in the form of particles or larger pieces. The wear in the cutting tool occurs in different structures depending on the material and structure of the machined part, the selected machining conditions and the process. As a result, all wear patterns change the geometry of the cutting edge. However, this change is determined according to the mechanism and creates different physical loads on the team. Below the literature review of machinability studies made by milling is presented.

Cutting parameter optimization with response surface methodology (RSM) with improved teaching learning based optimization (ITLBO) algorithm has been addressed by [17]. Li at all. state that cutting force increased by 2.70% and surface roughness decreased by 49.42%. The manufacturing success is mainly based on appropriate tool conditions [18]. Milling process monitoring has a great impact on energy saving, economy and increases processing quality. Authors proposed a tool condition monitoring method (TCM) for the milling process based on using a multisource pattern recognition model. The proposed model has been harmonious with experimental results. A novel ANFIS-PSO method has used to find qualified tool wear prediction model and obtain the best combination of machining parameters with prolong tool life [19]. It was claimed that prolong tool life could be guaranteed with optimized cutting parameters by random vibration and cross particle swarm optimization algorithm. Certain tool wear surveillance techniques are a very important perspective for manufacturing system success. The tangential force coefficient and flank wear correlations have been used to estimate tool wear [20]. Tool wear monitoring system is very important to evaluate tool wear status during milling operation [21]. The energy efficiency machining process can possible via physics-based prediction of tool wear timely and accurately [16, 22]. The physics-based machining model in Computer numerical control (CNC) measurements of cutting force can predict the power consumption. Accelerometer and dynamometer are used to gather signals from the milling machine. Long-distance milling is too hard for multi-tooth milling. Tool wear increases as increasing with longer cutting distance [23]. Authors seen that surface roughness was worse quality under long-distance cutting with lower feed rate relatively. Machining performance and tool wears on composites have been monitored with comparison of dry and LCO_2 machining conditions in [24]. Tool wear has been reduced 50% with using LCO_2 in comparison to dry machining. In addition, considering the 1000mm slot length, power consumption is reduced by reducing tool-chip friction. A comparative analysis of tool wear behaviours were conducted under the dry and cryogenic milling conditions [25]. Tool wear is increased by an average of 3% through cryogenic and dry machining, while good thermal conductivity efficiently supports cooling. The literature survey is summarized in Table 2. Below is a literature review for the surface roughness of machinability studies by milling.

Tool wear is an inevitable occurrence during the milling process, and it can have a significant impact on the machining performance, surface quality, and tool life. As the tool wears, its geometry changes, resulting in a decrease in cutting edge sharpness, an increase in cutting forces, and a degradation of surface finish [26].

The effect of tool wear on milling can be summarized as follows:

- ✓ Increase in cutting forces: as the cutting edge of the tool wears, the cutting forces increase due to a decrease in sharpness. This can lead to chatter, vibration, and poor surface finish [27].
- ✓ Decrease in material removal rate: as the tool wears, its cutting ability decreases, resulting in a lower material removal rate. This can increase machining time and decrease productivity
- ✓ Degradation of surface finish: as the tool wears, the surface finish of the workpiece can degrade due to an increase in tool deflection, chatter, and vibration [5].
- ✓ Tool life: tool wear reduces the life of the tool, which can lead to increased costs due to frequent tool replacement [28].

Table 2. Literature review of tool wear studies

Type of sensors	Machine	Process	Workpiece	Output parameters	Aim	Ref.
Dynamometer, surface roughness measuring instrument	CNC milling machine	Milling	EN AW 7050	Ra, MRR, SEC, cutting parameters	To obtain a milling power consumption model on account of tool wear with cutting conditions.	[17]
Dynamometer, Optical Microscope	CNC	Milling	CGI	Tool wear values for different cutting parameters	To reduce the energy consumption with controlling tool wear and machining paramters	[29]
Dynamometer, thermocouple, Optical microscope	CNC high-speed	Milling	Fiber-glass	Cutting zone temperature, cutting forces under GFRP in dry and LCO_2cutting conditions	Machining performance and tool wears have been monitored with comparison of dry and LCO_2 machining conditions.	[24]
Optical microscope, power analyzer, SEM	CNC	Milling	Ti-6Al-4V	Tool wear measurements, SEM EDS	Tool wear analysis under dry and cryogenic environment conditions.	[25]
Optical microscope, dynamometer	CNC milling	Milling	HRC52	Vibration of the workpiece, high-frequency acoustic emission signal	Tool wear were monitored using different types of cutting force signal data	[18]

Dynamometer, infrared thermal imager	CNC vertical machine	Milling	Inconel 718 Steel	Cutting force, tool wear differences with cutting pass	The tool wear monitoring model have been developed based on cutting force and cutting temperature	[20]
Dynamometer, Optical microscope	Vertical milling	Milling	C45 steel	Measured tool wear after each pass with tangential and radial force	The tool flank wear has been indirectly measured by correlating to the tangential cutting force and cutting parameters. Max. error has been estimated to be 8%.	[21]
Dynamometer, infrared sensor	CNC milling machine	Milling	AISI4340 steel	The machine power consumption and spindle power has been measured	A digital-twin model has been explored to defining the tool wear diagnosis with measuring the machine power.	[22]
Dynamometer, SEM, Digital microscope, focus microscope	CNC vertical machine	Milling	CFRP composite	Milling force, SEM	The machining performance has been evaluated based on tool wear	[23]

The effect of surface roughness in milling

During the chip removal process, it is necessary to consider the entrances to the machine and its exits along with other important operations included in the machine. These include the materials of the cutting tool, the workpiece material to be machined, and the rigidity of the machine. The roughness and precision of the processed material surface are important output parameters as they determine the final purpose of the material. Achieving precision on machined surfaces in machining is always one of the important parameters. The sensitivity of the surface is the term that encompasses many parameters, and these can be the finishing of the surface and the cleaning of cracks on the surface, thermal damage in the form of chemical change, burning, transformation and excessive tempering, and permanent tensile stress in the workpiece material [6]. The mechanism of regenerative excitation of vibrations occurs when the chip thickness during machining becomes comparable to the cutting edge radius of the tool [30]. This results in a phenomenon called "chip segmentation" or "serrated chip formation," where the chip is formed in discrete segments instead of a continuous chip [31]. As the chip thickness becomes smaller, the cutting edge periodically comes into and out of contact with the workpiece, causing the cutting forces to fluctuate. These fluctuations can cause the cutting tool to vibrate and can lead to the generation of regenerative chatter vibrations. A variable cutting speed can have a significant impact on the generation of regenerative vibrations. If the cutting speed is too low, the cutting forces may become unsteady, resulting in increased vibration amplitudes. On the other hand, if the cutting speed is too high, the chip thickness may become too small, leading to chip segmentation and the onset of regenerative chatter vibrations [32]. Regenerative vibrations can have a significant impact on the mechanical properties of the machined surface. The vibrations can cause plastic deformation of the material, resulting in the formation of surface defects such as chatter marks, waviness, and roughness. These defects can lead to reduced fatigue life, decreased wear resistance, and reduced dimensional accuracy of the machined surface quality [33].

The specific parameters recommended for measuring surface roughness can vary depending on the type of surface being measured and the intended application [5]. However, some commonly used parameters for characterizing surface roughness include [34]:

i. Ra (arithmetical mean roughness): the arithmetic average of the surface heights and depths within a measurement length.
ii. Rz (maximum height roughness): the distance between the highest peak and lowest valley within a measurement length.
iii. Rq (root mean square roughness): the square root of the mean of the squared heights and depths of the surface within a measurement length.
iv. Rt (total roughness): the distance between the highest peak and the lowest valley over the entire measurement length.

v. Rp (peak-to-valley height): the distance between the highest peak and lowest valley within a single measurement.

It is important to note that different parameters may be more appropriate for different applications, and some parameters may be more useful than others depending on the specific properties of the surface being measured. The surface roughness and profile are two main parameters for mechanical products. The good surface finish has great importance for the manufactured products. Generally, the researchers propose models that simulate the conditions during machining to overcome the problems of selecting conservative process parameters that do not guarantee the achievement of the desired surface finish or attain high metal removal rate [5]. These models establish the relationship between various factors and desired product characteristics, allowing for a more precise prediction of the outcome of the machining process.
With the advances of computer-controlled machine tools, there is a need for even more precise predictive models. These models can take into account a wide range of parameters, such as cutting speed, feed rate, depth of cut, tool geometry, and workpiece material properties, and simulate the machining process in a virtual environment. This allows for the optimization of machining parameters and the prediction of the surface finish and material removal rate, without the need for expensive trial-and-error experiments. Finite element method (FEM) is another important analysis method to evaluate the milling parameters [35, 36]. FEM involves simulating the machining process using complex mathematical models to predict the deformation and stress distribution in the workpiece and the tool. Analytical models use mathematical equations to predict the surface finish and tool wear, while empirical models are based on experimental data and use statistical methods to establish the relationship between process parameters and product characteristics. This method has enabled us to predict surface roughness instead of directly measuring from the values of cutting force. An experimental study was conducted to verify FEM analysis cutting force predicted by Jinge et al. [37]. They found that the analyses made were quite compatible with the experimental research. A deformation prediction FEM model accomplished under chip literature survey is summarized in Table 3. removed condition by Xi et al. [38]. Also, they performed an experimental study to verify the precision of the FEM model. An experimental study was conducted by Yadav et al. to optimize the cutting parameters in CNC milling via Taguchi method [39]. Analyses were conducted under boundary conditions such as cut and tool dimensions, cutting force, speed and superficial level hardness. A comprehensive review research is made by Meher et al. on CNC milling process with cutting conditions and environments [40]. The accurate prediction of surface roughness with the hybrid kernel method was proposed by Cheng et al. [41]. They have conducted the milling experiments to verify the prediction model under different cutting parameters and tool wear combinations. Consequently, they observed that the accuracy of hybrid kernel prediction models is higher than other prediction models, vector regression, Gaussian process regression. Chan et al performed to structural performance analysis and experimental verification to surface roughness in machining. A finite-element analysis method was used to determine the dynamic and static properties of the machine. Also, five-axis machine-tool cutting process was accomplished experimentally. Hence results showed that the surface roughness of the workpiece could be predicted very closely via AIM neural network prediction model [42]. Monitoring and estimating the surface quality during machining of workpieces that require high precision, especially used in the aerospace industry, is an important issue. A literature survey was done on online continuous tool wear monitoring for machining processes by Manivannan et al. [43]. The monitoring models determined by a cutting parameter often fail in different applications. For this reason an online monitoring milling model was suggested by Wang et al. to prediction on high value products [44]. A comprehensive review on empirical prediction of surface roughness was done by Deshpande et al. [45]. Li et al. performed the spindle speeds optimization study mainly based on cutting depth, cutting width parameters. Back propagation neural network (BPNN) regression model was used in optimization work. As a result an economical machining process has been recommended [46]. Perard et al. evaluated the milling cutters axial run out, teeth number and tilt angle sensitive have been characterized with surface roughness and residual stress [47]. The

Table 3. Literature review of surface roughness studies

Type of sensors	Machining operations	Process	Workpiece	Output parameters	Aim	Ref.
Dynamometer, Optical microscope,	5-axis CNC machining center	Milling	Haynes 230	Surface roughness	Monitoring tool wear input values used to predict the surface roughness	[41]
Load cell, sensor probe, displacement display meter, accelerometer, surface roughness meter, tool microscope	5-axis CNC vertical machine	Milling	Al-6061	Surface roughness measurments, Ra,	The surface roughness has been assessed under the trend of machine vibration condition	[42]
Microscope, surface roughness tester	CNC milling machine	Milling	Ti6Al4V	Tool wear value (VB), Surface roughness (Ra)	On-Line surface roughness prediction with integrating tool wear and cutting parameters various	[44]
Dynamometer, CMM	5-axis CNC machining center	Milling	SS-Grade420	CMM machine measures of surface roughness	26.2% reduction in surface roughness was observed with optimized virtual machining parameters.	[48]
Power meter, surface roughness tester	CNC machining center	Milling	Al3003	Measured of surface roughness	Surface roughness and energy saving machining have been proposed with machining parameters such; spindle 11,368.8333r/min, feed speed 3.7232m/min cutting with 0.3442mm and cutting depth 0.4846mm	[49]
Surface roughness tester	CNC vertical machine	Milling	Al6061-T6	Surface roughness measurements with coated and uncoated carbide tool	Machining parameters effects are investigated on surface roughness by Taguchi's method.	[50]
Surface roughness tester	CNC machhining center	Milling	Ti-6Al-4V	Surface roughness	Taguchi method have been used to obtain the optimum surface roughness quality	[39]
Dynamometer, confocal microscope	CNC verticalmachine	Milling	15-5PH martensitic Stainless steel	Surface roughness parameters (Ra), residual stress	Milling cutters axial runout, teeth number and tilt angle sensitive's have been characterized with surface roughness and residual stress.	[47]

It is important to note that different parameters may be more appropriate for different surface roughness determining applications, and some parameters may be more useful than others depending on the specific properties of the surface being measured. It's always a good idea to consult with experts in the field or consult relevant literature for guidance on the most appropriate parameters for a given application.

Surface roughness is main parameter on sustainability of milling in machining process. Surface roughness may be improved but energy consumption is increased, the environmental impact generated from power production is raised [51]. Also this may lead to more machining time and operation. Surface roughness is decisive parameter on sustainability performance of milling process [52]. Taguchi statistical method of design of experiments is generally prefered to determine the optimum parameter as seen in Table 3. Taguchi method provides to determine the optimum cutting parameters more efficiency and economically with minimum variation [53].

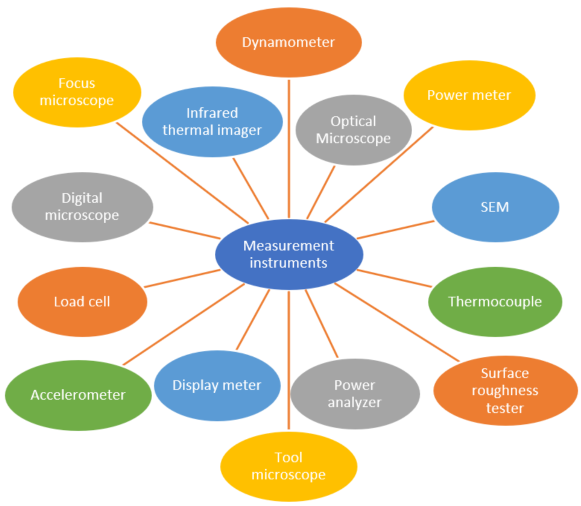

Fig. 2. The sensors used in the milling operations

Conclusions

Once the cutting process starts, the interaction between cutting tool and workpiece can produce different formed chips which play determinative role on the cutting mechanism and cutting variables. Therefore, the arrangement of the contact conditions determines the quality of the machining dynamics and machining outputs such as surface roughness, tool wear and cutting forces. The sensors generally used for machinability output parameters are given in Figure 2. A mathematical model of the machined surface can be used to predict the quality of machining by considering the cutting conditions and the level of vibrations. The model typically takes into account the following factors:

Cutting forces: The forces that act on the cutting tool during machining can be measured and used to predict the surface roughness. Higher cutting forces can lead to increased surface roughness.

Tool wear: As the cutting tool wears down, the surface roughness can become increasingly irregular. A model that takes into account the rate of tool wear can help predict the final surface quality.

Cutting speed: The speed at which the cutting tool moves across the workpiece can affect the quality of the machined surface. Higher cutting speeds can lead to increased surface roughness.

Vibration level: Vibrations can cause the cutting tool to chatter, resulting in uneven cuts and increased surface roughness. A model that takes into account the level of vibrations can help predict the final surface quality.

Material properties: The material being machined can affect the quality of the final surface. A model that takes into account the material properties, such as hardness and ductility, can help predict the final surface quality.

By combining these factors into a mathematical model, it is possible to predict the quality of machining for a given set of cutting conditions and vibration levels. This can help engineers optimize their machining processes to achieve the desired level of surface quality.

The use of predictive models can help to optimize the machining process and achieve the desired product characteristics, while minimizing the risk of cutter breakage and unsatisfactory surface finish.

The mechanism of regenerative excitation of vibrations occurs when the chip thickness during machining becomes comparable to the cutting edge radius of the tool. The vibrations can cause microstructural changes in the material due to cyclic loading. These changes can affect the mechanical properties of the surface layer, such as hardness, residual stresses, and microstructure. For example, the cyclic loading can cause grain refinement or coarsening, resulting in changes in the mechanical properties of the material. Therefore, it is important to carefully control the cutting speed to minimize the generation of regenerative vibrations and to optimize the machining process to achieve the desired mechanical properties of the machined surface.

To mitigate the negative effects of tool wear, several strategies can be employed. One approach is to monitor the tool wear and adjust the machining parameters, such as the cutting speed, feed rate, and depth of cut, to maintain optimal cutting conditions. Another approach is to use cutting tools with advanced coatings, such as diamond-like carbon (DLC), to improve tool life and performance. Additionally, the use of cooling and lubrication can reduce the temperature and friction between the tool and workpiece, which can help to reduce wear and increase tool life. Tool wear is a crucial factor to consider in milling, and understanding its effects can help to optimize the machining process, reduce costs, and improve surface quality.

The deductions made from this paper is summarized below:

- Seemingly, dynamometer is one the most used sensor to investigate the surface roughness in milling many types of materials such as Ti alloys, Al alloys, stainless steel etc. Monitoring of the cutting force changes helps to understand the distortions of the surface and the relationship between tool wear index allows for the determination of the surface characteristics of the materials.
- The utilization of the thermal imagers, accelerometers and dynamometers have been widely seen during monitoring of the tool wear characteristics. In the recent years, Ni alloys, Ti alloys and composites have been preferred and utilized for milling operations to analyze tool wear. Another important point in here is that SEM images have been gained importance to analyze the tool wear mechanisms.
- Cutting force measurements have been used to analyze the tool wear development in milling of different types of materials. Seemingly, especially for hard-to-cut materials were preferred to analyze in detail which can be explained with the reality that dynamometers can reflect the machining mechanism directly and helps to monitor the changes in tool wear.

References

1. Yaseer, A. and H. Chen, *Machine learning based layer roughness modeling in robotic additive manufacturing.* Journal of Manufacturing Processes, 2021. **70**: p. 543–552.
2. Korkmaz, M.E., et al., *Indirect monitoring of machining characteristics via advanced sensor systems: a critical review.* The International Journal of Advanced Manufacturing Technology, 2022: p. 1–36.
3. Ghazali, M.F., et al., *Tool wear and surface evaluation in drilling fly ash geopolymer using HSS, HSS-Co, and HSS-TiN cutting tools.* Materials, 2021. **14**(7): p. 1628.
4. Yaşar, N., et al., *A novel method for improving drilling performance of CFRP/Ti6AL4V stacked materials.* The International Journal of Advanced Manufacturing Technology, 2021. **117**(1): pp. 653–673.
5. Benardos, P. and G.-C. Vosniakos, *Predicting surface roughness in machining: a review.* International journal of machine tools and manufacture, 2003. **43**(8): p. 833–844.
6. Binali, R., *Sıcak iş takım çeliğinin (TOOLOX 44) işlenebilirliğinin incelenmesi.* Karabük Üniversitesi Fen Bİlimleri Enstitüsü, 2017.
7. Dhanda, M., et al., *On modelling and analysis of voxel-based force prediction for a 3-axis CNC machining.* Advances in Materials and Processing Technologies, 2022: p. 1–12.

8. Chen, X., et al., *Cutting force prediction between different machine tool systems based on transfer learning method.* The International Journal of Advanced Manufacturing Technology, 2022: p. 1–13.
9. Chen, Y., et al., *Modeling study of milling force considering tool runout at different types of radial cutting depth.* Journal of Manufacturing Processes, 2022. **76**: p. 486–503.
10. Shi, K.-N., et al., *Indirect approach for predicting cutting force coefficients and power consumption in milling process.* Advances in Manufacturing, 2022. **10**(1): p. 101–113.
11. Qin, S., et al., *CWE identification and cutting force prediction in ball-end milling process.* International Journal of Mechanical Sciences, 2022: p. 107863.
12. Wan, M., et al., *On material separation and cutting force prediction in micro milling through involving the effect of dead metal zone.* International Journal of Machine Tools and Manufacture, 2019. **146**: p. 103452.
13. Bernini, L., P. Albertelli, and M. Monno, *Mill condition monitoring based on instantaneous identification of specific force coefficients under variable cutting conditions.* Mechanical Systems and Signal Processing, 2023. **185**: p. 109820.
14. Mao, J., et al., *A material constitutive model-based prediction method for flank milling force considering the deformation of workpiece.* Journal of Manufacturing Processes, 2022. **84**: p. 403–413.
15. Grossi, N., et al., *A frequency-based analysis of cutting force for depths of cut identification in peripheral end-milling.* Mechanical Systems and Signal Processing, 2022. **171**: p. 108943.
16. Chen, X., et al., *A new method for prediction of cutting force considering the influence of machine tool system and tool wear.* The International Journal of Advanced Manufacturing Technology, 2022. **120**(3): p. 1843–1852.
17. Li, B., X. Tian, and M. Zhang, *Modeling and multi-objective optimization of cutting parameters in the high-speed milling using RSM and improved TLBO algorithm.* The International Journal of Advanced Manufacturing Technology, 2020. **111**(7): p. 2323–2335.
18. Dai, W., et al., *Tool condition monitoring in the milling process based on multisource pattern recognition model.* The International Journal of Advanced Manufacturing Technology, 2022. **119**(3): p. 2099–2114.
19. Xu, L., et al., *Prediction of tool wear width size and optimization of cutting parameters in milling process using novel ANFIS-PSO method.* Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2022. **236**(1-2): p. 111–122.
20. Liu, D., et al., *Tool wear monitoring through online measured cutting force and cutting temperature during face milling Inconel 718.* The International Journal of Advanced Manufacturing Technology, 2022. **122**(2): p. 729–740.
21. Choudhury, S. and S. Rath, *In-process tool wear estimation in milling using cutting force model.* Journal of Materials Processing Technology, 2000. **99**(1–3): p. 113–119.
22. Awasthi, U., et al., *Physics-based modeling and information-theoretic sensor and settings selection for tool wear detection in precision machining.* Journal of Manufacturing Processes, 2022. **81**: p. 127–140.
23. Bi, G., et al., *Wear characteristics of multi-tooth milling cutter in milling CFRP and its impact on machining performance.* Journal of Manufacturing Processes, 2022. **81**: p. 580–593.
24. Khanna, N., et al., *Comparison of dry and liquid carbon dioxide cutting conditions based on machining performance and life cycle assessment for end milling GFRP.* The International Journal of Advanced Manufacturing Technology, 2022. **122**(2): p. 821–833.
25. Khan, M.A., et al., *Comparative analysis of tool wear progression of dry and cryogenic turning of titanium alloy Ti-6Al-4V under low, moderate and high tool wear conditions.* The International Journal of Advanced Manufacturing Technology, 2022: p. 1-19.
26. Aslan, A., *Optimization and analysis of process parameters for flank wear, cutting forces and vibration in turning of AISI 5140: A comprehensive study.* Measurement, 2020. **163**: p. 107959.
27. Chuangwen, X., et al., *The relationships between cutting parameters, tool wear, cutting force and vibration.* Advances in Mechanical Engineering, 2018. **10**(1): p. 1687814017750434.
28. Moran, T., R. MacDonald, and H. Zhang, *A Dynamic Simulation Model for Understanding Sustainability of Machining Operation.* Sustainability, 2022. **15**(1): p. 152.
29. Xu, L., et al., *A novel intelligent reasoning system to estimate energy consumption and optimize cutting parameters toward sustainable machining.* Journal of Cleaner Production, 2020. **261**: p. 121160.
30. Biermann, D. and A. Baschin, *Influence of cutting edge geometry and cutting edge radius on the stability of micromilling processes.* Production Engineering, 2009. **3**: p. 375–380.
31. Rodríguez, J., J. Carbonell, and P. Jonsen, *Numerical methods for the modelling of chip formation.* Archives of Computational Methods in Engineering, 2020. **27**: p. 387–412.
32. Quintana, G. and J. Ciurana, *Chatter in machining processes: A review.* International Journal of Machine Tools and Manufacture, 2011. **51**(5): p. 363–376.
33. Peigne, G., et al., *Impact of the cutting dynamics of small radial immersion milling operations on machined surface roughness.* International Journal of Machine Tools and Manufacture, 2004. **44**(11): p. 1133–1142.
34. Thomas, T., *Characterization of surface roughness.* Precision Engineering, 1981. **3**(2): p. 97–104.
35. Kundrák, J., et al., *The energetic characteristics of milling with changing cross-section in the definition of specific cutting force by FEM method.* CIRP Journal of Manufacturing Science and Technology, 2021. **32**: p. 61–69.

36. Ali, M.H., et al., *FEM to predict the effect of feed rate on surface roughness with cutting force during face milling of titanium alloy.* Hbrc Journal, 2013. **9**(3): p. 263–269.
37. Jing, X., et al., *Modelling and experimental analysis of the effects of run out, minimum chip thickness and elastic recovery on the cutting force in micro-end-milling.* International Journal of Mechanical Sciences, 2020. **176**: p. 105540.
38. Xi, X., et al., *A prediction model of the cutting force–induced deformation while considering the removed material impact.* The International Journal of Advanced Manufacturing Technology, 2022. **119**(3): p. 1579–1594.
39. Yadav, D.K., et al., *Optimization of surface roughness by design of experiment techniques during CNC milling machining.* Materials Today: Proceedings, 2022. **52**: p. 1919–1923.
40. Meher, J., et al., *Recent research development of CNC based milling machining conditions: A comprehensive review.* Materials Today: Proceedings, 2022.
41. Cheng, M., et al., *Prediction and evaluation of surface roughness with hybrid kernel extreme learning machine and monitored tool wear.* Journal of Manufacturing Processes, 2022. **84**: p. 1541–1556.
42. Chan, T.-C., H.-H. Lin, and S.V.V.S. Reddy, *Prediction model of machining surface roughness for five-axis machine tool based on machine-tool structure performance.* The International Journal of Advanced Manufacturing Technology, 2022. **120**(1): p. 237–249.
43. Manivannan, R., R. Rajasekar, and M. Maheswaran. *A review on online continuous tool wear monitoring system for machining process*. in *AIP Conference Proceedings*. 2022. AIP Publishing LLC.
44. Wang, Y., et al., *Online Surface Roughness Prediction for Assembly Interfaces of Vertical Tail Integrating Tool Wear under Variable Cutting Parameters.* Sensors, 2022. **22**(5): p. 1991.
45. Deshpande, A.A. and M.A.A. Rehman, *Surface Roughness Prediction using Empirical Modelling Techniques:-A Review.* SAMRIDDHI: A Journal of Physical Sciences, Engineering and Technology, 2022. **14**(01 SPL): p. 108–117.
46. Li, W., et al., *A novel milling parameter optimization method based on improved deep reinforcement learning considering machining cost.* Journal of Manufacturing Processes, 2022. **84**: p. 1362-1375.
47. Perard, T., et al., *Experimental investigation on surface integrity in a face milling operation.* Procedia CIRP, 2022. **108**: p. 400–405.
48. Soori, M., et al., *Minimization of surface roughness in 5-axis milling of turbine blades.* Mechanics Based Design of Structures and Machines, 2021: p. 1–18.
49. Yang, J., et al., *Multi-objective optimization of milling process: exploring trade-off among energy consumption, time consumption and surface roughness.* International Journal of Computer Integrated Manufacturing, 2022: p. 1–20.
50. Masooth, P.H.S., V. Jayakumar, and G. Bharathiraja, *Experimental investigation on surface roughness in CNC end milling process by uncoated and TiAlN coated carbide end mill under dry conditions.* Materials Today: Proceedings, 2020. **22**: p. 726–736.
51. Kant, G. and K.S. Sangwan, *Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining.* Journal of cleaner production, 2014. **83**: p. 151–164.
52. Jia, S., et al., *Multi-objective parameter optimization of CNC plane milling for sustainable manufacturing.* Environmental Science and Pollution Research, 2022: p. 1–22.
53. Gupta, A., H. Singh, and A. Aggarwal, *Taguchi-fuzzy multi output optimization (MOO) in high speed CNC turning of AISI P-20 tool steel.* Expert Systems with Applications, 2011. **38**(6): p. 6822–6828.