Journal of New Technology and Materials (JNTM)
J. New Technol. Mater.
Vol. 12, N°02 (2022)15-26

OEB Univ. Publish. Co.

Cutting tool wear prediction in machining operations, a review

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Received date: June 17, 2022 ; accepted date: Oct. 9, 2022

Abstract

In the machining process, tool wear is an unavoidable reason for tool failure. Tool wear has an impact on not just tool life but also the quality of the finished product in terms of dimensional accuracy and surface integrity. Tool wear is a significant element in the annual cost of machining. It happens when the tool-work contact zone experiences abrupt geometrical damage, frictional force, and heat generation. It's essential to accurately evaluate tool wear during machining so that the cutting tool can be replaced before the workpiece surface sustains significant damage. The capacity to assess tool wear is crucial for ensuring high-quality workpieces. Artificial neural network, Deep learning and Machine learning systems, heat generation analysis, image data processing, finite element method and gaussian process are used in order to accurately predict the tool wear during machining operations. In this paper, cutting tool wear prediction in machining operations is reviewed in order to be analyzed and minimized. The main purpose of the study is to provide a useful resource for researchers in the field by presenting an overview of current research on cutting tool wear prediction in machining processes. As a consequence, the research area can be progressed by reading and assessing existing achievements in published articles in order to provide new ideas and methodologies in prediction and minimization of tool wear during machining operations.

Keywords: Cutting tool wear, Cutting tool life, Cutting Temperatures

1. Introduction

Mechanical work is transformed to plastic deformation in machining processes, resulting in friction between the cutting tool and the workpiece and increased heat output. Tools get stressed over time because they are constantly in touch with high friction and rubbing [1]. Tool wear is a natural phenomenon that occurs on cutting tools as a result of mechanical, chemical, and thermal stresses during machining processes. Tool wear refers to the progressive deterioration of cutting tools as a result of constant usage during chip formation process which can raise the cutting force and causes more machining mistakes, lowering the quality of the machined surface [2]. Many parameters, including as chemical composition, microstructure, and heat treatment, impact the machinability of tool wear. Mechanical restrictions such as abrasion or erosion, as well as chemical interactions that damage the materials, such as corrosion, are the two primary sources of wear [3]. Different wear of cutting tool as flank wear, notch wear, and crater wear zones of the cubic boron nitride cutting insert are shown in Figure 1 using a scanning electron microscope [4].

Cutting tool wear has a significant impact on the material's capacity to be shaped as well as the cost of manufacturing the final product. The values of induced residual stress, strain, subsurface energy, and machined surface quality are all affected by tool wear [5]. Increased tool wear causes materials to soften and wear to increase fast, affecting tool life, machining efficiency, and accuracy. In the continuous cutting process, the tool temperature rises as the speed of machining increases. As tool wear increased, residual tension and strain beneath the machined surface increased as well [6].

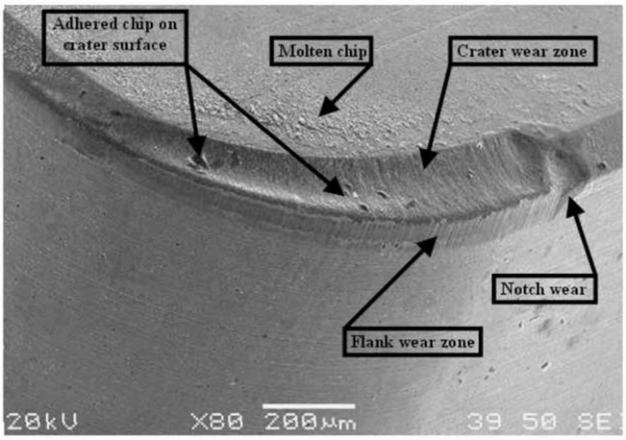

Figure 1. Flank wear, notch wear and crater wear zone for the cubic boron nitride cutting insert [4].

Increased cutting pressures, increasing cutting temperatures, poor surface smoothness, decreased completed part precision, tool breakage, and altering tool geometry are all results of tool wear. The use of lubricants and coolants when machining can help to reduce tool wear [7]. Tool wear is minimized as a result of reduced friction and temperature. When the wear size hits a critical value, the machined surface's surface roughness decreases, cutting force and temperature increase rapidly, and the wear rate increases [8]. According to published studies on metal cutting, the three parameters that have the greatest influence on tool wear and life are cutting speed, feed rate, and depth of cut. The feed rate, followed by spindle speed and cut depth, has the largest influence on tool life [9, 10].

The component of the tool in touch with the final part erodes due to flank wear [11]. Crater wear occurs when the rake face is eroded by contact with chips during machining operations. This is typical with tool wear, and it does not noticeably limit the tool's utility until it reaches a point when the cutting edge fails. A spindle speed that is too low or a feed rate that is too high can cause crater wear to the cutting tool during machining operations. When cutting orthogonally, this usually happens where the tool temperature is the highest. Crater wear occurs at a height that is about equivalent to the material's cutting depth [12, 13].

Notch wear occurs along the depth of the cut line on both the insert rake and flank face, generating localized damage mostly due to pressure welding of the chips [14]. The chips are fused to the insert in this way. Material being machined builds up on the cutting edge, creating a built-up edge. Aluminum and copper, for example, have a tendency to anneal themselves to a tool's cutting edge. It's more common on softer metals with a lower melting point.

Gowthaman et al. [15] evaluate the machinability and tool wear mechanism of Duplex stainless steel in order to improve cutting tool life during machining operations. Review of recent methods for tool wear reduction in electrical discharge machining is presented by Gill et al. [16] to decrease tool wear by recently developed techniques or modifications. Artificial intelligence systems for tool condition monitoring in machining operations is reviewed by Pimenov et al. [17] to enhance the dimensional accuracy and productivity in the machined components. To predict and avoid adverse conditions for cutting tools and machinery, the deep learning methods in analysis and minimization of tool wear is reviewed by Serin et al. [18]. Surface integrity induced by tool wear effects in machining process of titanium and nickel alloys is reviewed by Liang et al. [19] to increase surface quality of machined parts. Wang et al. [20] examine the tool wear mechanism and suppression method in diamond turning of ferrous materials in order to achieve high-quality workpiece surface integrity. Sivalingam et al. [21] provide Machining Behaviour, Surface Integrity, and Tool Wear Analysis in Environmentally Friendly Turning of Inconel 718 Alloy to minimize cutting temperature and tool wear during turning operations. Enhanced particle filter method is used by Wang et al. [22] in order to predict the cutting tool wear during chip formation process. To minimize the tool wear and surface roughness during machining operations, the Taguchi optimization method is applied by Kara [23]. In order to improve the accuracy and reliability of tool wear prediction techniques during machining operations, a unique approach of analyzing and forecasting coated cutting tool wear during Inconel DA 718 turning is given [24]. In order to provide an enhanced tool wear monitoring system, tool wear prediction while machining with self-propelled rotary tools is provided [25].

Soori et al. provide virtual machining approaches for evaluating and improving CNC machining in virtual environments. [26-29]. Soori and Arezoo presented a study of modern virtual machining systems in order to improve the influence of virtual simulation and analysis on component manufacturing efficiency [30]. Soori and Arezoo proposed a review in machining generated residual stress to assess and decrease residual stress during metal cutting operations [31]. Soori et al. present an overview of current improvements in friction stir welding techniques in order to investigate and enhance the efficiency of component production processes that use welding procedures [32]. Soori and Asmael investigated the mechanical behavior of materials during machining processes in order to improve the quality of manufactured products [33]. Soori and Asamel investigated the use of virtual machining technologies in turbine blade five-axis milling procedures to minimize residual stress and deflection error [34]. Soori and Asmael developed virtualized machining systems for analyzing and lowering cutting temperatures during milling operations on difficult-to-cut components [35]. To enhance surface qualities during five-axis milling operations of turbine blades, Soori et al. developed an improved virtual machining approach [36]. To decrease deflection error during five-axis milling procedures of impeller blades, Soori and Asmael invented virtual milling approaches [37]. In order to investigate and enhance the parameter optimization approach for machining operations, Soori and Asmael offered a synopsis of existing advances from published works [38]. Dastres et al. investigate RFID-based wireless manufacturing systems to increase energy efficiency, data quality and availability throughout the supply chain, and precision and reliability during the component manufacturing process [39].

Dastres and Soori are researching developments in web-based decision support systems in order to build decision support systems for data warehouse management [40]. Dastres and Soori present a review of recent development and applications of artificial neural networks in various areas such as risk analysis systems, drone control, welding quality analysis, and computer quality analysis in order to develop artificial neural network applications in various areas such as risk analysis systems, drone control, welding quality analysis, and computer quality analysis [41]. Applications of the information communication technology in the environmental protection is presented by Dastres and Soori [42] in order to decrease the effects of technology development to the natural disaster.

In this paper, a review in prediction and minimization of cutting tool wear in machining operations is presented and future research works are also suggested. Different methods of tool wear prediction such as artificial neural network, machine learning systems, cutting temperature considerations, image data processing, finite element method, energy considerations, multi-sensor fusion, support vector machines and gaussian process are discussed in the paper. Also, the different methods of tool wear minimization are presented in the paper in order to provide new ideas from the published papers in terms of tool wear minimization during chip formation process.

2. Cutting tool wear prediction

It is critical to accurately predict tool wear during machining so that the cutting tool can be replaced before substantial damage to the workpiece surface occurs. The ability to evaluate tool wear is critical for ensuring that the workpiece is of excellent quality [43]. In industry, tool wear prediction is critical for increased productivity and product quality. The cutting tool's condition is critical for manufacturing quality, and its failure can result in major issues [44,45]. The ability to accurately estimate the rate of tool wear improves process efficiency and allows for tool replacement before catastrophic wear occurs [46]. Controlling tool wear rate is crucial in both metal cutting and metal shaping because it impacts component geometry, surface, and subsurface integrity [47]. Tool wear assessment and service life prediction are critical for achieving sustainable manufacturing because they provide scientific basis for critical decisions such as maintenance scheduling and inventory management [48].

2.1. Artificial neural network

Artificial Neural Networks (ANNs) are a type of machining process that predicts tool wear and surface roughness. Model development is employed when regression models fail to generate satisfactory results [49]. The use of artificial neural networks (ANNs) in an on-line approach for tool wear monitoring has been proposed. Cutting velocity, feed, cutting force, and machining time are all sent into the ANN, which then estimates flank wear. To properly estimate tool wear, several ANN architectures are built and evaluated [50]. In face milling of aluminium matrix composite materials (AMC), which are categorized as hard-to-cut materials, artificial neural networks are utilized to anticipate tool wear (ANN) [51]. Figure 2 shows the structure of a multilayer perceptron (MLP) network for tool wear prediction [51].

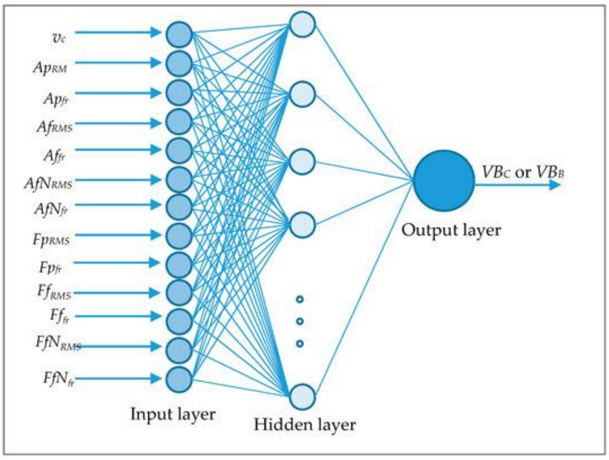

Figure 2. Multilayer perceptron (MLP) network system for tool wear assessment [51].

The sophisticated tool wear surveillance system is provided to suggest tool wear monitoring methodologies based on convolutional neural networks as a reference for academics and companies [52]. A real-time monitoring approach for a tool's wear state based on a convolutional bidirectional LSTM model is proposed in order to give an enhanced way of tool wear prediction utilizing an artificial neural network [53]. For real-time monitoring of tool wear state, Figure 3 displays a neural network architecture based on a convolutional neural network (CNN) and a bidirectional long short-term memory (BiLSTM) network with an attention mechanism [53].

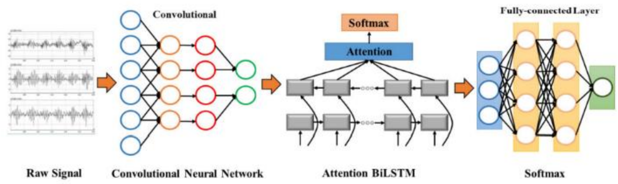

Figure 3. Framework for real-time tool wear monitoring using neural networks [53].

Prediction of Tool Wear in Ti-6Al-4V Machining using PCA Features and Multiple Sensor Monitoring The purpose of Pattern Recognition is to boost the productivity of machining processes by lowering the rate of cutting tool failure [54]. To improve the accuracy of cutting tool wear prediction, the vector support machine for wear rate estimation was developed. [55]. During hardened steel turning processes, artificial neural networks are employed to alter cutting tool wear prediction techniques [56]. The goal of developing a physics-guided neural network for machining tool wear prediction is to overcome the physical inconsistency that exists in traditional data-driven tool wear prediction approaches [2]. Tool wear prediction utilizing cutting force and surface roughness is provided using an artificial neural network in order to reduce tool wear during harsh turning operations of EN8 steel alloys [57]. Iterative neural network convergences for tool wear prediction during turning operations are described in order to reduce tool wear prediction errors throughout the chip production process. [58]. To improve the accuracy of tool wear prediction methodologies during machining processes, artificial intelligence approaches are used to anticipate cutting tool wear during the milling process [59]. Utilizing acoustic emission and cutting power statistics, artificial neural network systems are used to provide enhanced tool wear detection in the milling operation [60]. Tool wear monitoring using deep learning method and multi-domain feature fusion is described in detail in order to accurately estimate tool wear during milling [61].

2.2. Deep learning and machine learning systems

In order to effectively anticipate cutting tool wear during machining processes, time series imaging and deep learning are used to classify tool wear [62]. Figure 4 depicts a framework for tool wear classification that combines time series imagery and deep learning [62].

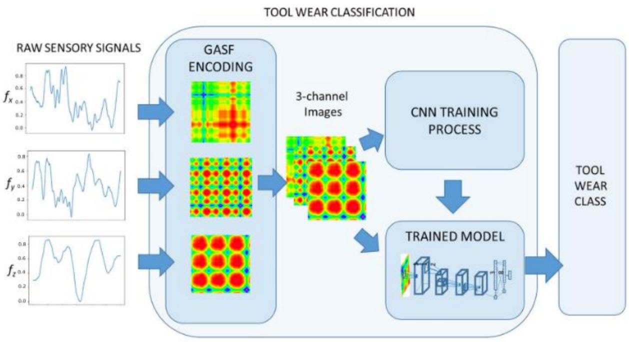

Figure 4. Framework incorporating time series imagery and deep learning for tool wear classification [62].

In order to enhance tool wear prediction outcomes, deep learning-based tool wear prediction and its implementation for machining processes utilizing multi-scale neural network classifier and channel attention technique are explained [63]. Figure 5 depicts a flowchart of the intelligent tool wear monitoring system [63]. Tool-wear forecasting and pattern identification using artificial neural networks and DNA-based computing is presented to enable superior tool-wear monitoring in material removal operations [64]. In monitor tool wear circumstances during the chip production process, powerful machine learning algorithms are used to predict tool wear size across several cutting situations [65].

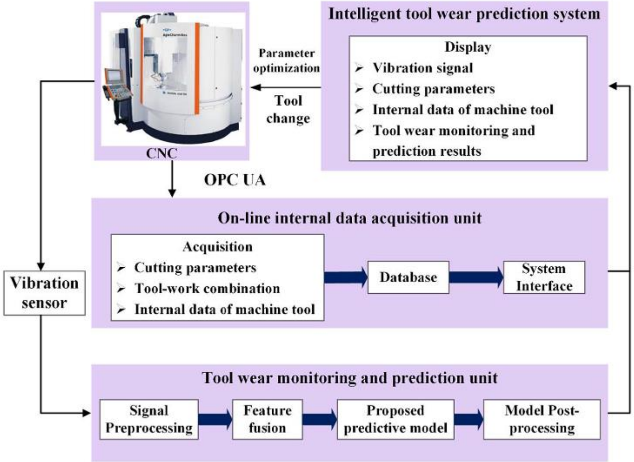

Figure 5. Diagram of the intelligent tool wear monitoring system [63].

In order to improve tool wear prediction accuracy, a predictive model based on least - square support vector machines and machine learning techniques is described [66]. The use of multifractal detrended analytics and a support vector machine to monitor tool condition in milling operations is suggested in order to enhance productivity by lowering the rate of cutting tool failure during milling operations [67]. Tool wear monitoring using wavelet package decomposition and a new gravitational search approach least square support vector machine model is provided to increase milling efficiency [68]. In order to offer sophisticated tool monitoring systems throughout the chip formation process in turning high strength steel, a smart prediction model of tool wear machine learning algorithms utilizing linear regression is provided [69].

In order to give better prediction accuracy and good predictive performance in tool wear prediction approaches, multi-sensor feature fusion dependent on stacked sparse autoencoders is used in milling tool wear forecasting [70].

Figure 6 depicts the proposed model's network structure for predicting tool wear using multisensor characteristics [70]. An intelligent tool wear tracking and multi-step forecasting based on a deep learning model is suggested to minimize the rate of cutting tool damage during machining operations [71]. The use of heterogeneous sensors-based feature optimization and deep learning for tool wear estimation is detailed in order to increase predictive performance in tool wear tracking systems [72]. The mechanism of tool wear and anticipation in milling TC18 titanium alloy is described using deep learning in order to produce a better online tool monitoring system [73].

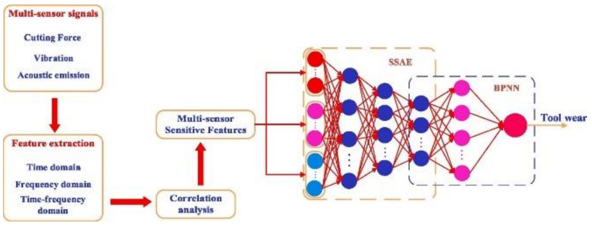

Figure 6. The network framework of the proposed model in prediction of tool wear using multi sensor features [70].

The use of long short-term memory modelling to anticipate tool wear in high-speed turning of a steel alloy is discussed in order to provide enhanced tool monitoring systems during milling processes [74]. A monitoring and predicting system based on multiscale deep learning techniques and fog computing is being proposed to enhance the reliability and accuracy of tool wear prediction methodologies [75]. To estimate tool wear during milling operations, a deep heterogeneous GRU model for data analytics in smart factory has been used [76]. A tool wear state excellent understanding on feature-based transfer learning is suggested in order to properly forecast tool wear throughout the chip manufacturing process. [77].

2.3. Cutting temperature considerations

During chip tool interactions and material chip removal, the cutting fluid has a propensity to remove heat. Cutting fluid allows for a considerable temperature range during machining, resulting in a heat cycle, which can contribute to longer insert and cutting tool life as well as good chip breaking [78]. In order to accurately anticipate cutting tool wear during milling processes, research on tool wear detection based on temperature signals and deep learning is given [79]. Figure 7 depicts the architecture of the proposed model for tool wear predictions based on temperature signals and deep learning [79].

In order to enable real-time control over the surface layer characteristics during machining, a measurement system based on the Seebeck effect for determining temperature and tool wear during turning of aluminium alloys is provided [80]. A study on temperature rise, tool wear, and surface roughness during drilling of al–5%sic composite is presented in order to accurately evaluate the tool damage, workpiece damage, and chip formation during machining operations [81]. In order to account for the wear progress during the chop generation process, an enhanced numerical technique on tool wear modelling for tool and process design incorporating cutting temperatures in metal cutting operations is described [82]. In order to construct and test a prediction model of tool wear in milling operations, audio signals and machine learning are used to monitor tool wear [83]. A prediction model for the milling of thin-wall parts considering thermal-mechanical coupling and tool wear condition is presented in order to increase accuracy of machined components [84].

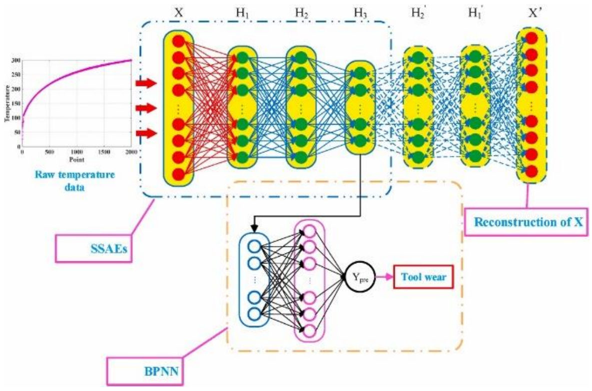

Figure 7. The presented model's architecture for tool wear assessment based on temperature inputs and deep learning [79].

In order to provide a rapid, reliable, and physics-based technique for the prediction of flank tool wear in laser-assisted milling of diverse materials, an analytical predictive model based on cutting temperature for flank tool wear in laser-assisted milling is proposed [85].

2.4. Cutting tool image data processing

In order to provide improved tool wear prediction systems, neural networks and image processing are used to anticipate tool life in turning operations. In order to detect the condition of tool wear in a flexible production cell setting, tool-wear analysis employing image processing of the tool flank is provided [86]. Figure 8 depicts images obtained at various points during the processing process to highlight the phases of tool wear [86].

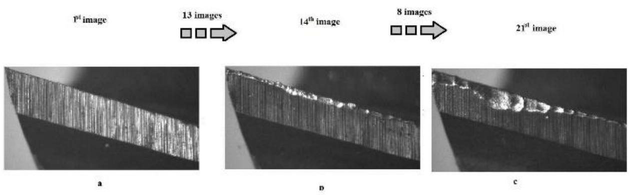

Figure 8. Images taken at successive times during processing showing the stages of tool wear [86].

Digital image processing with deep learning for automated cutting tool wear detection is presented in order to provide fully automated cutting tool wear analysis method using machine tool integrated microscopes in the scientific and industrial environment [87]. To monitor tool wear in micro milling operations, advanced image processing method is presented [88]. The application of image processing algorithms to monitor tool wear in turning is discussed in order to improve the accuracy of on-line tool wear analysis throughout the chip creation process [89]. In order to enable automatic tool wear detection utilizing standard photos of cutting tools, image data processing through neural networks for tool wear prediction is provided [90]. In order to build the Tool life prediction approach during machining operations, a mix of tool chip image processing and evolutionary fuzzy neural network is given [91].

2.5. Finite element method

Although experimental and analytical examinations have traditionally been the primary techniques of investigating tool wear, the advancement of computers and Finite Element (FE) methodologies now allows tool wear to be predicted using chip formation simulations [92]. In order to offer an effective device in the cutting tool wear prediction approach, a mesh node stiff moving algorithm for the uncoated milling cutter tool wear prediction considering periodic process factors is described [93]. Figure 9 depicts the tool wear prediction procedure using a FEM model [93].

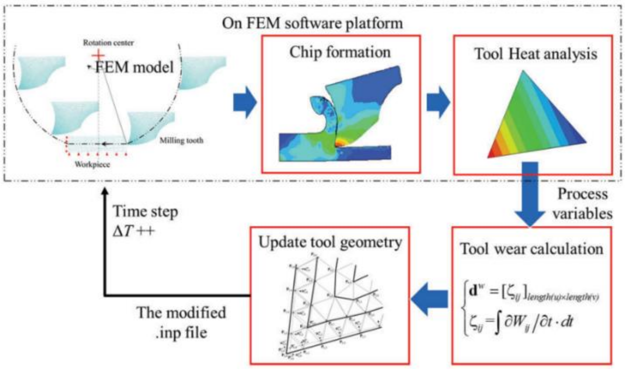

Figure 9. Tool wear prediction process in FEM model [93].

A combination experimental and statistical strategy based on the finite element approach is introduced for machining tool wear predictions in order to increase accuracy and reliability [94]. FE-based tool wear modelling is used on complicated shaped and coated cutting tools in turning operations to accurately predict tool wear during machining processes [95]. A 3D FEM modelling of tool wear in ultrasonic assisted rotary cutting is presented to reduce cutting tool damage and failure in turning operations [96]. To improve the accuracy and reliability of tool wear prediction systems, a numerical and experimental examination of tool wear in turning operations is given [97]. A finite element estimate of tool wear effects in ti6al4v machining is developed in aim is to reduce the percentage of cutting tool failure during machining operations [98]. The impact of cutting circumstances (including cooling conditions) on tool wear is evaluated using a numerical simulation of tool wear in drilling Inconel 718 under flood and cryogenic cooling conditions [99]. Simulated (upper) and experimental (bottom) of tool wear in drilling Inconel 718 is shown in the figure 10 [99].

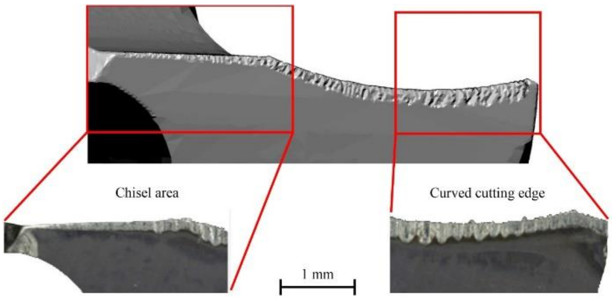

Figure 10. Simulated (upper) and experimental (bottom) of tool wear in drilling Inconel 718, t = 21 min [99].

To investigate the impacts of machining settings on cutting tool life, a finite element approach for the wear assessment of cemented carbide tools during high-speed Ti6Al4V cutting is provided [100]. The finite element approach is used to evaluate tool wear in rotary turning that has been changed by ultrasonic vibration machining processes [101]. To analyze the effects of cutting temperature to the cutting tool wear, the finite element simulation is applied [102].

2.6. Gaussian process

To enhance the prediction of tool remaining usable life during machining operations, a technique for forecasting the remaining useful life of cutting tools in varied cutting circumstances based on a Gaussian process regression (GPR) model incorporating a tool wear mechanism is described [103]. In order to accurately estimate cutting tool wear under a range of cutting situations, Gaussian process regression for tool wear prediction is examined [104]. The GPR model's flowchart for predicting tool wear is shown in the figure 11 [104]. Using a symmetrized dot pattern and multi-covariance analysis, a tool wear prediction approach was developed. In order to improve the accuracy of cutting tool wear prediction methods, Gaussian process regression is provided [105]. Continuous tool wear prediction based on Gaussian mixture regression model is presented in order to provide accurate methods of tool wear prediction during machining operations [106]. The use of an inverse gaussian process model to forecast the useful life of cutting tools is presented in order to increase cutting quality and productivity during machining operations [107].

In order to create tool wear prediction techniques during machining operations, force-based tool wear estimate for milling processes utilizing gaussian mixed hidden markov models is provided [108]. To provide the tool wear condition monitoring in real industrial environment, force sensor based online tool wear monitoring using distributed gaussian ARTMAP network is presented [109]. To increase the accuracy of the tool wear prediction methods, tool wear condition monitoring based on continuous wavelet transform and blind source separation is presented [110]. In order to extend the cutting tool life during machining operations, a tool wear prediction assessment in milling based on multi-sensory data is provided [111]. In order to develop a smart tool wear prediction model in woven composites drilling, Gaussian process regression and artificial neural networks are applied [112].

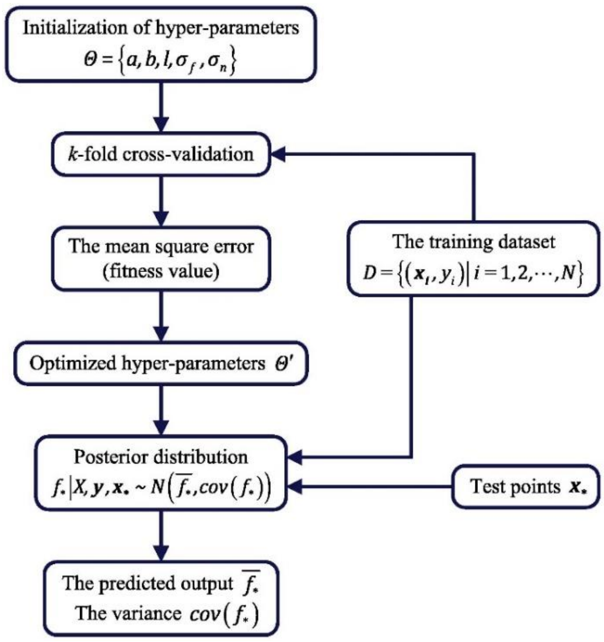

Figure 11. The GPR model's flowchart for predicting tool wear [104].

3. Conclusion

Tool wear remains of high interest for industry, since it has an impact on process costs and component surface integrity. Thermal fracturing, attrition, abrasion, plastic deformation, diffusion, and grain-pull out all contribute to machining tool wear during the metal cutting process. If the machining process is continued with a worn tool, dimensional accuracy, finished component surface quality, and even process stability will suffer. As a consequence, the requirement for tool wear monitoring prediction systems in sophisticated manufacturing sectors is highly recognized for the goal of improving quality and productivity. Tool wear has a significant impact on the values of induced residual stress, strain, subsurface energy, and the machined surface quality. As tool wear increased, residual tension and strain beneath the machined surface increased as well.

Applications of the tool wear prediction in the smart manufacturing systems and industry 4.0 can be developed in order to increase productivity of part production by decreasing the cutting tool failure during machining operations. Digital twin approach within Industry 4.0 framework for advanced tool wear monitoring systems can be presented in order to increase the impacts of smart minoring systems in productivity enhancement of part production.

New materials of cutting tool inserts can be analysed by the advanced tool wear prediction systems in order to analyze and decrease the wear rate in the modified cutting tool inserts. The effects of shapes and angels of new cutting tool inserts to the cutting forces as well as tool wear can be studied in order to minimize the tool wear during machining operations. Application of the optimization methods to the parameters of cutting tool and machining operations can be analyzed in order to minimize the tool wear during machining operations.

The accuracy as well as reliability of the analytical tool wear models can be analyzed by using the mathematical modelling in order to increase the accuracy of the tool wear prediction using the analytical tool wear models. The impact of tool wear on surface integrity (including residual stresses) can be studied using different tool materials, workpiece materials, and lubricant conditions in order to reduce tool wear during machining operations.

Advanced signal processing techniques can be applied to the outputs of corresponding sensors during tool wear monitoring systems in order to increase the accuracy of the online cutting tool wear monitoring tools. Vibration and sound signals of the cutting tool during chip formation process can be analyzed in order to provide advanced tool wear prediction technique. Also, the encoder signals as well as spindle motor current, feed motor current can be used in terms of developing the tool wear prediction methodologies in order to decrease the cutting tool failure during machining operations. The colour of the chip in the machining operations as well as chip morphology can be utilized by using the advanced image processing techniques in order to decrease the tool failure rate during machining operations. Different tool wear patterns can be obtained in the different machining conditions in order to be minimized.

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