Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 115 (2022) 232–240

www.elsevier.com/locate/procedia

10th CIRP Global Web Conference – Material Aspects of Manufacturing Processes

Recent advances in modelling and simulation of surface integrity in machining – a review

Amir Malakizadi[a,*], Rachele Bertolini[b], Francois Ducobu[c], Z.Murat Kilic[d], Maria Chiara Magnanini[e], Alborz Shokrani[f]

[a] Department of Industrial and Materials Science, Chalmers University of Technology, SE-412 96, Gothenburg, Sweden
[b] Department of Industrial Engineering, University of Padova, Via Venezia 1, 35131, Padova, Italy
[c] Research Institute for Science and Material Engineering, University of Mons, Place du Parc 20, Mons, Belgium
[d] Department of Mechanical, Aerospace and Civil Engineering, University of Manchester, Oxford Rd, Manchester, M13 9PL, United Kingdom
[e] Department of Mechanical Engineering, Politecnico di Milano, Via La Masa 1, 20156, Milan, Italy +46-31-7726377
[f] Department of Mechanical Engineering, University of Bath, Bath, BA2 7AY, United Kingdom

* Corresponding author. Tel.: +46-31-772 63 77. *E-mail address:* amir.malakizadi@chalmers.se

Abstract

Machining is one of the final steps in the manufacturing value chain, where the dimensional tolerances are fine-tuned, and the functional surfaces are generated. Many factors such as the process type, cutting parameters, tool geometry and wear can influence the surface integrity (SI) in machining. Being able to predict and monitor the influence of different parameters on surface integrity provides an opportunity to produce surfaces with predetermined properties. This paper presents an overview of the recent advances in computational and artificial intelligence methods for modelling and simulation of surface integrity in machining and the future research and development trends are highlighted.

© 2022 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 10th CIRP Global Web Conference –Material Aspects of Manufacturing Processes (CIRPe2022)

Keywords: Surface integrity, FEM; Machining dynamics; CFD; Artificial intelligence; Machine learning

1. Introduction

A growing challenge in the aerospace, automotive and biomedical industries is to manufacture the high-end components in line with the UN sustainable development targets enforcing higher resource efficiency, reduced environment impacts and carbon footprint along the value-chain. It is well documented that the performance and functionality of a manufactured component, e.g. its fatigue endurance, corrosion resistance, wear properties, etc., is largely determined by the state of its machined surfaces, such as roughness, process-induced surface residual stresses (RS), etc. [1-3]. However, the stringent demands on machined surface quality can pose a challenge for the manufacturers to meet the sustainable development targets mentioned earlier. This is because the workpiece material is subjected to severe thermo-mechanical loads during machining processes that can trigger various temperature- and deformation-induced phenomena such as surface damage (pits, tears, laps, protrusions) and surface and sub-surface microstructural alteration (white-layer formation and recrystallisation). These thermal (elevated temperatures followed by rapid quenching) and mechanical (high stresses, strains and strain rates) effects are the main reasons for the microstructural alteration in the materials and the development of tensile RS near the machined surfaces [1]. Hence, it is of vital importance to: 1) understand the fundamental relationship between the parameters associated with machining process namely, cutting conditions, tool material and micro-geometry, wear and cooling-lubrication strategies and the resultant machined surface characteristics; and 2) develop models and approaches that facilitate the implementation of zero-defect manufacturing strategies [4] to avoid the unexpected failure of machined components during their applications. Considering the novelty and numerosity of

2212-8271 © 2022 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 10th CIRP Global Web Conference –Material Aspects of Manufacturing Processes (CIRPe2022)
10.1016/j.procir.2022.10.079

the currently available approaches to improve surface integrity, a fast and reliable method is needed to identify the effect of the aforementioned parameters on the machined surface quality in advance. This would allow for determining the optimum process conditions and achieving the most desirable surface integrity characteristics. Recent progress in numerical modelling such as finite element analysis has shown great potential to be adapted for modelling and simulation of surface integrity. In addition, recent advances in artificial intelligence (AI) and the realisation of deep learning algorithms for signal processing propelled by the developments in hardware capabilities have enabled monitoring and modelling of machining performance with a potential for real time process control.

The aim of this review article is to provide a comprehensive but synthetic overview of modelling and simulation methodologies of surface integrity in machining. In particular, methodologies are critically discussed with respect to industrial applicability and the challenges towards industrial implementation to proactively and predictively determining the effect of process parameters on SI. Therefore, the analytical and semi-analytical approaches such as those proposed by Schoop et al. [5] and Baizeau et al. [6] are not the focus of the current review paper. This is because the applicability of these approaches is not sufficiently investigated. Despite this, the potential of physics-informed AI approaches incorporating such analytical and semi-analytical modelling methods have been acknowledfed in the summary and outlook.

This paper provides an overview of twofold strategies viable to achieve the desirable SI in machining. Firstly, advanced computational methods for proactively determining the state of machined surfaces are introduced and discussed; this mainly includes Finite Element Method (FEM) but also the recent advances in Meshless methods and application of Computational Fluid Dynamics (CFD) in the field, as shown in Fig.1. Particular attention is also devoted to shed the light on the importance of machining dynamics and simulation of process kinematics for modelling SI in machining. Secondly, the application of AI algorithms for monitoring and predicting SI is proposed. On one hand, these methods have the advantage of being able to be integrated with feedback and feedforward control loops, though they struggle in generalization due to the need for extensive data-driven validation, as it will be explained.

Whilst the focus of this review paper is placed on metal cutting processes, the approaches discussed here can, in principle, be extended to other processes such as grinding. Finally, in the concluding section, the main outcomes of the critical analysis are summarised, and promising research directions are enounced to allow sustainable development for machined components within the whole lifecycle.

2. Advanced computational methods

2.1. FEM and meshless methods – continuum simulations

The mechanical response of a metallic material during the cutting process is directly linked to its microstructure and its evolution. It therefore influences the surface integrity of the component, which motivates its inclusion in numerical models of machining [7, 8]. Modelling the material behaviour in cutting still mostly relies on phenomenological relations, although the physics-based (dislocation-based) models have recently become the focus of several studies. Johnson-Cook constitutive and damage models are still widely adopted, mainly due to their availability in the commercial FE codes such as ABAQUS®, SFTC DEFORM® and AdvantEdge® [7, 8]. FEM uses a mesh and is the most adopted approach to model the cutting processes so far. Several formulations ranging from pure Lagrangian to pure Eulerian have been used for cutting simulation. In the Lagrangian formulation, the material is tied to the mesh, leading to mesh distortions for simulating large material deformations occurred during machining. On the contrary, the movement of the material is independent of the mesh in the Eulerian formulation. Eulerian formulation is mainly used for steady-state modelling and not adopted when surface integrity is considered. The Arbitrary Lagrangian Eulerian (ALE) formulation combines these two modelling strategies and enables a relative movement between the material and the mesh. Whilst using ALE can reduce mesh distortion, it cannot entirely eradicate it [9, 10]. On the other hand, the Coupled Eulerian-Lagrangian (CEL) formulation takes advantage of the Eulerian formulation to solve the elements distortion in the workpiece [11]. Remeshing techniques h introduced to avoid mesh distortion. Remapping of the solution between the meshes can however reduce the accuracy of the solution [10].

Meshless methods have also been developed to mainly overcome the problem of the element distortion due to large deformations encountered during cutting process and to handle crack formation. Smoothed particle hydrodynamics (SPH) [12] is nowadays the most used method for meshless modelling and simulation of the cutting processes. The Discrete Element Method (DEM) [13], the Finite Pointset Method (FPM) [14] and the Particle Finite Element Method (PFEM) [15] are showing promising results, while they are barely applied to cutting. These methods are computationally expensive and therefore access to high performance computing resources (e.g., parallel computing, GPU) is deemed necessary [16, 17]. To date, no application of meshless methods to SI modelling has been reported in the literature.

Orthogonal cutting, resembling broaching operation, is the most modelled machining setup due to its simplicity as compared to the complex kinematics and tooling configurations commonly used under operational conditions. The modelling and simulation of orthogonal cutting process has become a well-accepted strategy for investigating the influence of various parameters – including tool micro-geometry, tool wear geometry, cutting conditions and cooling-lubrication – with large impacts on SI of machined components.

Most of the literature on modelling and simulation of surface integrity is focused on metallic materials [18]. However, drilling of composite materials, especially CFRP and CFRP/metal stacks, has recently gained a lot of interest. Modelling the influence of fibre orientation when orthogonal cutting CFRP laminate allowed marked improvements in the surface quality and reduced sub-surface damage [19, 20]. Xu et al. [21] simulated the orthogonal machining of CFRP/Ti6Al4V stacks using a 3D Lagrangian modelling strategy, where the fibres and the matrix were explicitly included in the FE model. This investigation revealed the role of sequence of the material stacks (CFPRP/Ti6Al4V or Ti6Al4V/CFRP) in cutting temperatures and surface quality (e.g., the amount of uncut fibres), and the damage at the interface of the materials.

For metals, Liu et al. [22] studied the influence of tool geometry on residual stresses (RS) for Alloy 718 using a CEL model. Their simulation followed the experimental trends and the results were within the range of experimental deviations when varying the rake angle, edge radius and flank wear to provide insight into the mechanism of RS generation. The influence of the coating on the magnitude of RS for Alloy 718 and AISI 316L is modelled by Outeiro et al. [23], indicating that RS are higher when using the uncoated tool. Özel and Ulutan [24] also considered the influence of cutting tool geometry and coating when machining Ti6Al4V and IN100 alloy. The developed 3D FE model showed that the increase of the edge radius led to more compressive RS, while coating the tool resulted in more tensile RS. The capabilities of Lagrangian and CEL modelling approaches are evaluated by da Silva et al. [25] for modelling RS when machining Alloy 718. Both modelling approaches provide good results in the cutting direction; however, Lagrangian formulation seems to provide slightly better predictions in the perpendicular direction. The Lagrangian formulation is adopted to investigate the surface deformation when machining Ti6Al4V [26]. The effect of chip segmentation on RS distribution and surface topography is studied using a CEL model when machining Alloy 718 [27]. It showed that the formation of a segmented chip generates periodic mechanical and thermal loadings on the machined surface, resulting in a waved surface and cyclic RS. The influence of friction and material constitutive models on the reliability of the RS prediction is highlighted by Outeiro et al. [28]. The authors recommend designing experimental tests dedicated to the identification of friction coefficients and material constitutive parameters. Several studies also proposed the implementation of more elaborated phenomenological constitutive models to improve the reliability of RS predictions. For example, the constitutive model implemented by Xu et al. [29] resulted in differences of less than 5% between the experimental and the numerical cutting forces thanks to a more realistic thermomechanical behaviour of the machined material. The morphology of the numerically produced segmented chips was also closer to the experiments than with the classical Johnson-Cook law. Cyclic variation of the machined surface topology and RS is also observed when segmented chips are generated. In parallel, several physics-based models are proposed for simulation of the microstructure changes (grain size and hardness) on the machined surfaces induced during machining various metallic alloys [30, 31].

Arrazola et al. [18] stated that an increasing number of studies are dedicated in recent years to modelling 3D operations closer to the industrial needs, such as drilling, turning and grooving. For example, Xu et al. [29] compared 2D and 3D free orthogonal cutting of Ti6Al4V to highlight the influence of lateral burr on the stress, plastic strain and temperature. The results demonstrated the superiority of 3D simulations. Longitudinal turning [32] and grooving [33] are simulated using a hybrid (3D) model based on a 2D local ALE model. However, several cutting revolutions should be simulated to reach the steady state condition, allowing the

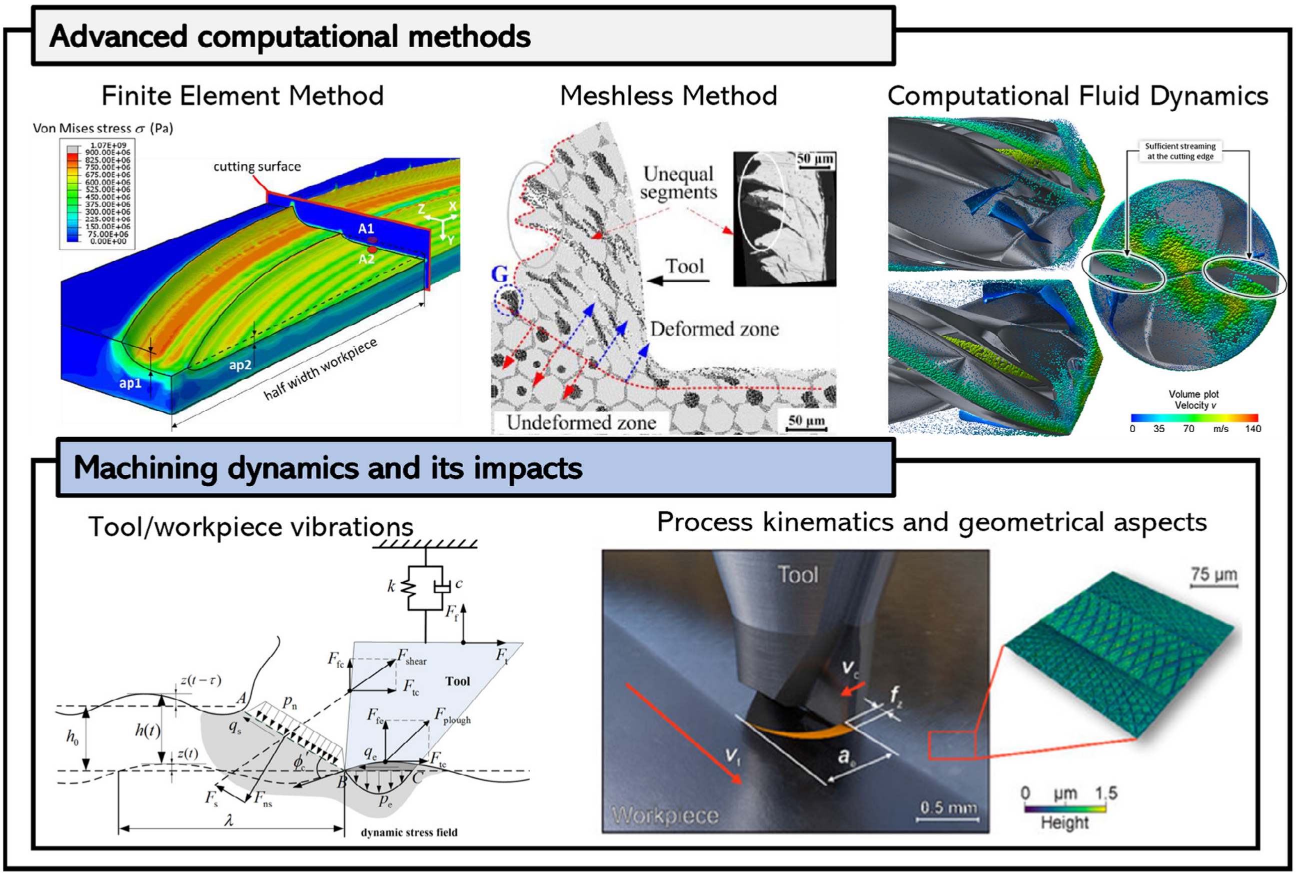

Fig. 1: Schematic overview of the Section 2 on advanced computational methods, including the effects of machining dynamics on SI [13, 34, 48, 51, 65]

modelling of the surface topography (including surface roughness) and the prediction of RS. Vovk et al. [34, 35] developed a 3D CEL model of milling for AISI 4140. The authors introduced a multi-pass or sequential cuts approach that takes the influence of the previous cuts into account to determine RS, temperature and forces at the current cut, as shown in Fig.1. This is a step further to a realistic simulation of an industry-relevant model. The CEL formulation is also adopted by Zhuang et al. [36] to investigate the influence of the ratio of the uncut chip thickness on the tool edge radius on RS (together with cutting forces, chip morphology and temperatures) for AISI 304 stainless steel. The sequential cuts are also included in this investigation. The authors showed that the RS profile becomes approximately constant after a certain number of cuts; however, this phenomenon depends on the cutting condition and tool micro-geometry. Single and double cut influence on the RS development when machining Ti6Al4V is studied by Yue et al. [37] using a CEL model. A reduction in the magnitude of the RS is observed with an increase in the number of cuts.

Despite significant advancement in recent years, an in-depth analysis of the published data in the literature suggests that neither FE or meshless methods are sufficiently mature to provide reliable predictions when machining under operational conditions. This is partly because of the complex metallo-thermo-mechanical phenomena involved in the vicinity of cutting edge – some of which are still not well understood, e.g., the relative impacts of microstructural softening/alteration and damage evolution on material response during the chip formation process [38, 39]. In addition, modelling strategy and numerical formulation, and an appropriate representation of constitutive and damage models can all play marked impacts on the reliability of the predicted results. Yet, there are other less investigated factors involved that can influence the accuracy of numerical simulations. For example, as the microstructural alteration is concerned, the kinetics of the solid phase transformations, dynamic recovery and recrystallisation is not readily available at the practical ranges of strain, strain rate and reasonable time scales during the cutting process. Often the required kinetic and the physical properties of the parent and transformed phases, such as flow stress properties of hcp and bcc phases in Ti-6Al-4V, are taken from studies concerning forming and thermal treatments. The lack of reliable material data may lead to unreliable outcomes. The other factor that may affect the accuracy of the model predictions is the thermal boundary conditions. Essentially, the reliability of numerical simulations depends on an accurate representation of the boundary conditions applied on the surfaces subjected to the cooling media and at the tool-chip interface. Whereas the impact of lubrication is normally included in numerical models by altering the friction coefficients of an appropriate model [40], the cooling effects are generally taken into account using the constant or variable (e.g., temperature dependent) heat transfer coefficients (HTC) on the respective surfaces [41]. However, the convection HTC are either obtained using costly inverse approaches based on embedded thermocouples (and thermographic data) [41] or are determined using oversimplified empirical relationships as a function of dimensionless numbers such as Nusselt number, Reynolds number and fluid Prandtl number [42].

To overcome these limitations, several studies have proposed utilising CFD to obtain the convection HTC to be later applied on the numerical models to provide a more reliable estimation of the thermo-mechanical loads in machining. These studies investigated the heat transfer when machining under different cooling-lubrication conditions, e.g., MQL [43-45], cryogenic (LN_2 or CO_2) [46, 47] and emulsion [48]. Yet most studies have placed their focus on simulation of heat transfer in the vicinity of cutting edge with the aim to develop simulation-assisted strategies for cooling channel design or optimisation of associated parameters (e.g., cooling pressure, temperature) to increase the tool performance in terms of tool life or to investigate various cutting zone phenomena. The resulted improvements in tool wear management can indirectly lead to a better control of SI parameters in practice. For example, Oezkaya et al. [48] used a CFD-assisted approach to investigate the role of cooling pressure and nozzle diameter when drilling Alloy 718. The authors observed that the Reynold's number at the severely loaded regions of the drill remains nearly unchanged with an increase of the nozzle diameter by 25%, despite distinctly higher mass flux when using the tool with larger nozzle diameter – thus nozzle diameter showed to have minimal cooling effects. The cooling pressure, on the other hand, had a marked impact on tool life and the quality of the machined surfaces. The authors also claimed that the higher cutting fluid velocities at higher cooling pressures led to improved convection and thus better tool life and bore surface qualities. Iovkov et al. [49] later used the knowledge gained based on this CFD-assisted strategy to re-design and modify the tool geometry – resulted in improved tool life, better temperature control and thus improved bore quality (e.g., roundness). These studies showcase how effectively CFD can be implemented to estimate the heat transfer on the machined surfaces and to determine the boundary conditions required for improved temperature predictions and thus more accurate estimation of RS and microstructural alteration.

2.2. Modelling machining dynamics and its impacts

Vibrations are inevitable in machining systems not only when machining large depths of cut, but it is also challenging to perform machining when the cutter or workpiece is flexible, such as in blisk machining when using long tools or machining difficult-to-cut and flexible materials. Hence dynamics of machining concern the quality of the machined component under the influence of the vibration characteristics of the machine tool/workpiece as well as the time-varying characteristics of the machining process. This section reviews the analytical efforts while including important experimental studies with new findings.

The surface roughness in turning and milling is, to a large extent, controlled by the process kinematics (i.e., tool orientation, tool path, feed direction and stepover distance) and cutting tool geometry, so the feed marks and cusp heights were the most important concerns of the initial analytical studies on surface topography simulations with rigid body assumption [50, 51]. Including the tool wear [52] is also important as the flank face slides on the generated surface, and it can thus change the surface topography of the machined components. The introduction of relative tool/workpiece displacement [53] into the simulation opened the dynamics era in surface topography simulations. In addition to the static deformations, the dynamic effects include the forced vibrations in relation to the natural frequencies of the tool/workpiece system. As the surface roughness results from the cumulative effects of rigid body motion and relative tool/workpiece vibrations in the system, for a stable chatter-free machining operation, one needs to superpose the vibrations on top of the rigid body motion [54, 55]. With the help of the semi-discretization method [56] that is originally formulated for checking chatter-free conditions, a general and complete milling simulation model would also include the forced vibrations in calculating surface location error (SLE) at an instant when the machined surface is generated on the workpiece [57]. Additionally, improvement in system and process models would certainly increase prediction accuracy for a wide range of cutting conditions (e.g., depths of cut and spindle speeds) and cutting tool materials (e.g., CBN and carbide) [58]. For the unwanted chatter vibrations, the tool may start jumping out of the cut and lose contact during machining; the superposition fails due to the nonlinear cutting action. In multi-mode systems, the mode-coupling effect may be linked to the regenerative effect. Seguy et al. [59] argued that this can give an advantage to the mode that is started first until a node of the same mode is encountered; they observed a strong link between vibrations and roughness and concluded that more dedicated research is required. The surface roughness pattern may repeat itself if the tool run-out is large enough. Zhenyu et al. [60] modelled this phenomenon during (face) milling operation where the axial run-out inevitably affects the surface roughness. The authors showed that the surface roughness repeats at every spindle rotation period, instead of tooth passing period, due to the axial runout between the inserts. Niu et al. [54] have developed a detailed model to explain the generation mechanism of surface topography, and concluded that surface roughness is very sensitive to teeth runout and pitch angle variation. A recent study by Yan et al. [61] reviewed comprehensively the methods to keep the surface quality under control in blade machining.

For the ultrasonic vibration-assisted (UV-assisted) machining technology, the surface roughness is not only attributed to the natural frequencies of the system, but also to the intended relative tool/workpiece motion. Chen et al. [62, 63] simulated the topography of machined surfaces during a UV-assisted helical milling operation. UV-assisted machining led to a marked increase (more than 63.5%) in compressive RS generated on the hole surfaces as compared to that of traditional helical milling. When the RS is concerned, majority of the investigations assume the tool-workpiece system is static and stationary, i.e., the tool is rigid and there is no relative motion between the workpiece and the tool other than the shearing action separating the chip from the workpiece. However, as mentioned above, machining systems are not ideal (rigid) in practice, and process vibrations do exist. A few studies have considered the effect of process vibrations on the RS developed on the machined surfaces [64-67]. Outeiro et al. [67] studied the effects of process dynamics on the RS formation. The authors provided controlled vibrations of the tool and monitored the resulting surface roughness and RS. For the first time, they observed that both surface roughness and RS vary periodically. Chomienne et al. [64] investigated the RS fluctuations in a real vibrating system. The authors set up a flexible component for a turning operation and measured RS of various machined samples. A clear difference between stiff and flexible turning workpiece samples was evident: the flexible sample exhibited very high deviations in both RS and surface roughness values, whereas the stiff sample showed very similar surface integrity from one sample to another. Maurotto and Tunc [68] also worked with a real milling system but they evaluated the effect of chatter vibrations on the resultant RS. Similar to the investigation by Outeiro et al. [67], Huang et al. [65] studied the cyclic development of surface residual stresses during turning operation. The feed rate was oscillated at 10 Hz between high and low values, resulting in varied uncut chip thickness. The trends of RS generation were well predicted. It was further reported that the largest variation in RS occurs when the largest variation in uncut chip thickness is imposed during the cutting process. Similar to the study conducted by Lin and Chang [69] for controlling the surface roughness, Kamada and Sasahara [66] investigated the influence of the vibration frequency ratio between the frequency of vibrations and spindle speed; they found that the RS variation can be eliminated at specific values.

Research on modelling the dynamics of machining process aims to increase the speed and accuracy of simulating the chatter stability, forced vibrations, dimensional surface errors as well as surface roughness in machining processes. The research on exploring the vibrations and tool geometry causing cyclic surface roughness inspired further studies on RS. The recent literature showed that there is a strong relationship between the process vibrations and RS of the machined component, though there are not many analytical studies explaining the dynamic effects on surface roughness and RS. Therefore, dedicated models for various machining operations and tool/workpiece pairs are required to investigate how vibrations can be used and controlled in order to achieve the required SI.

3. Artificial intelligence for predicting surface integrity

Modelling and simulation of surface integrity in machining is still mostly limited to orthogonal cutting process, as mentioned in Section 2.1. This limitation has encouraged researchers to develop data-driven methodologies and algorithms for the prediction of SI indicators. Whilst classical statistical methods such as regression have been used for modelling/predicting various parameters such as surface roughness, they are usually limited to specific machining conditions and cannot be generalised. Microstructure alteration, surface and sub-surface deformation, residual stresses and surface damage are often more complex to be pinned only to cutting parameters. Surface integrity parameters are dependent on many time-varying factors beyond cutting parameters such as tool wear, vibrations, cutting temperature, etc. To enhance the fit and improve prediction performance, shallow networks such as artificial neural network (ANN), hidden Markov, Bayesian and fuzzy expert systems (FES) have been used to correlate historical data with machining parameters. Majority of these methods have been used for tool condition monitoring with ANN being the dominant network for surface roughness prediction [70]. These models are used in lieu of regression models to minimise prediction errors. In this approach, specific surface integrity parameters are measured off-line and then correlated with various cutting parameters. Afterwards, a combination of cutting parameters is selected to achieve the desired surface integrity in machining. For instance, Khoshaim et al. [71] performed a series of machining experiments and assessed the residual stresses after turning pure iron samples. The authors used three types of

ANN to correlate the residual stresses to the cutting parameters and reported over 99% coefficient of determination. Karpat and Özel [72] used ANN to formulate a correlation between cutting parameters, surface roughness and residual stresses with less than 5% error on the test data. Multi-objective optimisation based on particle swarm optimisation was used to identify the optimum cutting parameters to achieve the desired surface integrity whilst maximising material removal rate or tool life. Kosarac et al. [73] performed a full factorial design of experiments with varying cutting parameters and used the experimental data for training an ANN for predicting average surface roughness Ra. They reported a mean squared error (MSE) of 0.0025 for an ANN trained with a Bayesian regularisation algorithm. Training shallow ANN networks with offline data from experiments for predicting surface roughness and optimising cutting parameters has received significant attention over the past 20 years. Obvious shortcomings are the limited generalisation capabilities, ignoring dynamic errors and time dependent variables such as tool wear. Structured DoEs are designed with a regression model in mind. When applied for training AI networks, they are prone to missing crucial information on machining performance. Pontes et al. [74] performed a critical review of using ANN shallow networks for predicting surface roughness. They highlighted that almost all papers reviewed used cutting parameters as input to their ANN models aiming to predict average surface roughness. It has become apparent that achieving higher accuracy in predicting surface roughness and controlling cutting parameters to reach a prescribed surface condition is not possible by solely considering cutting parameters as an input and ignoring time-varying parameters. This has necessitated using sensors to collect real-time data from machining as additional input parameters for modelling. Acoustic emissions, cutting forces and temperature have been used to feed models on surface roughness, RS and sub-surface properties. In contrast to training networks on offline historical data, indirect sensor signals during machining can be processed with artificial intelligent networks to monitor and control various surface integrity parameters. Azouzi and Guillot [75] used ANN to fuse multi-sensor signals for monitoring and predicting surface roughness Ra. They reported 2% to 25% errors in predicting surface roughness and noted that factors other than cutting parameters affect the machining condition and their influence needs to be taken into account. They used cutting forces, vibrations, acoustic emission and tool deflection sensors to take the impacts of cutting fluid, tool wear, tool-workpiece stiffness and variation in material properties into account [75]. Motta et al. [76] performed 92 turning experiments and collected surface roughness as well as cutting force, temperature and vibration signals. They compared Random Forest (RF) and Gaussian Process Regression (GPR) in their capability to predict surface roughness and concluded that GPR outperformed RF resulting in RSME of 0.4 µm. Mohring et al. [77] trained a convolutional neural network (CNN) to predict surface roughness based on a vibration sensor signal from the cutting tool. They reported an accuracy of 96% in predicting average surface roughness. Similarly, Lin et al. [78] used the vibration signal from a sensor positioned on the spindle of a milling machine to train and test a number of deep learning models to predict surface roughness. They concluded that while Fast-Fourier-Transform Long-Short-Term-Memory (FFT-LSTM) network performs best for higher values of roughness, a one-dimensional convolutional neural network (1-D CNN) is more suitable for predicting lower values of surface roughness. Fang and Pai [79] proposed using wavelet transfer packet integrated with ANN to predict surface roughness using cutting parameters as well as cutting force and vibration sensor signals. A set of 54 experimental data was used for training and testing the network with no

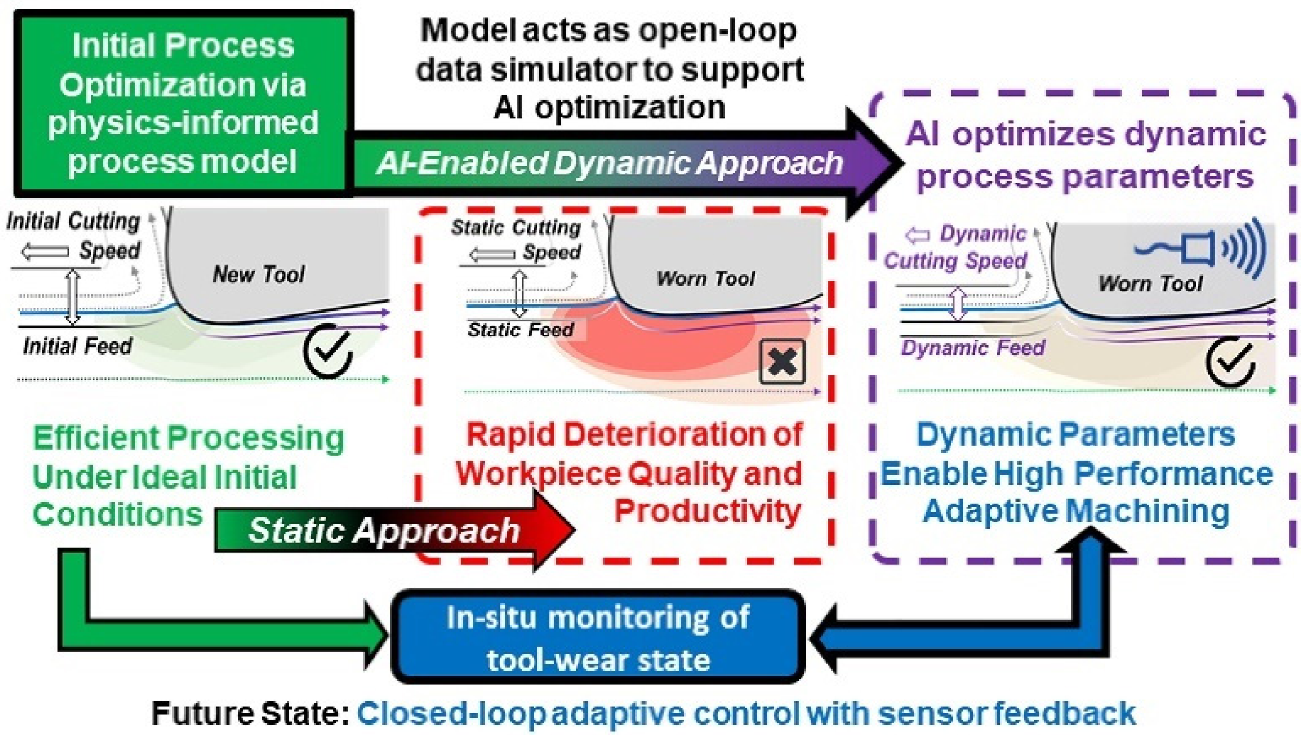

Fig. 2: Schematic of a physics-informed AI dynamic process parameter optimisation framework enabling improved tool wear control and SI as compared with static (off-line) approach [86].

details on validation data. Wang et al. [80] used a RF classifier to correlate acoustic emissions (AE) to machining conditions in orthogonal cutting of natural fibre-reinforced plastic. They performed a series of orthogonal cutting experiments using unidirectional composites at different fibre orientations. The proposed method was capable of predicting material cutting mode and detecting fibre fracture and debonding using the AE signal. Knittel et al. [81] used cutting forces in milling honeycomb cores with thin cell walls to train different types of learning algorithms to classify surface flatness into two categories: 1) best surface quality and 2) worst surface quality. They concluded that the support vector machines (SVM) preformed best when using labelled cutting force signals in supervised learning compared with k-nearest neighbour (KNN) and decision tree (DT) algorithms [81].
Deep learning networks are specifically powerful tools for image processing. In 1998, Tsai et al. [82] proposed using an ANN for predicting surface roughness based on images taken from machined surfaces illuminated with a structured light source. Rifai et al. [83] trained a CNN for predicting surface roughness based on images taken from machined surfaces. Liu et al. [84] developed a setup for on-machine scanning of machined surfaces in diamond turning using scattered light and a photodiode. A CNN was trained to detect surface defects on the machined surfaces. Bhandari and Park [85] used labelled microscopic images of machined surfaces and cutting parameters to train a CNN to classify machined surfaces into fine, smooth, coarse and rough categories. This is one of the few publications which shared the data and codes along with the paper. Whilst the use of shallow artificial networks has resulted in improved prediction performance and reducing errors, they still fail to capture dynamic and time dependant parameters affecting surface integrity. The combination of cutting parameters with live sensor signals together with deep learning analysis of the signals have a clear advantage in capturing the complexities of machining induced surface integrity. Combined with real time control, they have the potential to realise manufacturing of prescribed surface integrity. Surface defects such as plastic deformation, smearing, etc. are not quantifiable to be modelled and predicted using conventional statistics and shallow neural networks. Artificial Intelligence methods such as classifiers are capable of detecting and predicting these phenomena in machining based on additional sensor signals. Nevertheless, one of the major shortcomings of research publications on using artificial intelligent data-driven methods is the lack of data for training, testing, and cross-validation. Generating and collecting meaningful, repeatable, and reproducible experimental data can be costly and time consuming. Moreover, the data and the models used in published literature are often not available, limiting the possibility of cross-validation.

4. Summary and outlook

In recent years, the modelling and simulation tools have been used more effectively to address some of the key industrial challenges associated with the surface integrity of machined components, e.g., RS development, microstructural alteration, surface and sub-surface deformation and surface roughness. Whilst there are numerous successful examples reported in the literature, the industrial realisation of these computational approaches is still limited. A successful example is in cutting tool manufacturing, where these modelling techniques are more commonly used in the product development stages to minimise the need for experimental tests and the associated costs and efforts required for introducing a new tool grade/geometry. This is because these modelling approaches are often computationally very expensive and achieving reliable predictions still demands significant efforts, e.g., a careful selection of well-defined constitutive, damage and friction models and thermal boundary conditions. These limitations have led to the advent of sensor-based and data-driven methods, often classified under the AI umbrella. While AI algorithms provide powerful means to develop models based on historical data, the inclusion of real-time sensor data can enhance the accuracy of predictions. Specifically, tool wear and cutting temperature can affect surface integrity beyond cutting parameters. Similar methods used for tool condition monitoring using sensor data can be used to enhance prediction and control of surface integrity leading to machining of prescribed surfaces. Nevertheless, the integration of the continuum modelling and sensor-based data-driven approaches, i.e., physics-informed AI, is deemed necessary to benefit from the strength of both strategies, an example of which is shown in Fig. 2 [86]. This necessitates the development of reliable, efficient and robust hybrid (FE-based or semi-analytic) methods [5, 6, 32, 33] for the prediction of SI indicators such as RS and microstructural alteration to be integrated with AI algorithms. We expect this field of research to expand in the future.

Acknowledgements

This review article is an outcome of a collaborative initiative within the framework of CIRP Research Affiliate Programme. The authors have contributed to the same extent during the preparation of the manuscript. Amir Malakizadi would like to acknowledge the supports received from Chalmers Centre for Metal Cutting Research (MCR). Alborz Shokrani would like to acknowledge the support of the UK Engineering and Physical Sciences Research Council through EP/V055011/1.

References

[1] Z. Liao, A. la Monaca, J. Murray, A. Speidel, D. Ushmaev, A. Clare, D. Axinte, R. M'Saoubi, Surface integrity in metal machining - Part I: Fundamentals of surface characteristics and formation mechanisms, International Journal of Machine Tools and Manufacture, 2021; 162:103687.
[2] A. la Monaca, J.W. Murray, Z. Liao, A. Speidel, J.A. Robles-Linares, D.A. Axinte, M.C. Hardy, A.T. Clare, Surface integrity in metal machining - Part II: Functional performance, International Journal of Machine Tools and Manufacture, 2021; 164:103718.
[3] A. Malakizadi, D. Mallipeddi, S. Dadbakhsh, R. M'Saoubi, and P. Krajnik, Post-processing of additively manufactured metallic alloys – A review, International Journal of Machine Tools and Manufacture, 2022; 179:103908.
[4] D. Powell, M. C. Magnanini, M. Colledani, and O. Myklebust, Advancing zero defect manufacturing: A state-of-the-art perspective and future research directions, Computers in Industry, 2022; 136:103596.
[5] J. Schoop, D. Adeniji, and I. Brown, Computationally efficient, multi-domain hybrid modeling of surface integrity in machining and related thermomechanical finishing processes, Procedia CIRP, 2019; 82:356-61.
[6] T. Baizeau, F. Rossi, G. Poulachon, and J. C. Outeiro, Prediction of surface integrity using Flamant–Boussinesq analytical model, CIRP Annals, 2016; 65(1):81-84.

[7] H. Liu, X. Xu, J. Zhang, Z. Liu, Y. He, W. Zhao, Z. Liu, The state of the art for numerical simulations of the effect of the microstructure and its evolution in the metal-cutting processes, International Journal of Machine Tools and Manufacture, 2022; 177:103890.

[8] S. Melkote, S. Liang, T. Özel, I. S. Jawahir, D. A. Stephenson, and B. Wang, A Review of Advances in Modeling of Conventional Machining Processes: From Merchant to the Present, Journal of Manufacturing Science and Engineering, 2022; 144:11.

[9] F. Ducobu, E. Rivière-Lorphèvre, and E. Filippi, Numerical contribution to the comprehension of saw-toothed Ti6Al4V chip formation in orthogonal cutting, International Journal of Mechanical Sciences, 2014; 81:77-87.

[10] A. Malakizadi, K. Hosseinkhani, E. Mariano, E. Ng, A. Del Prete, and L. Nyborg, Influence of friction models on FE simulation results of orthogonal cutting process, The International Journal of Advanced Manufacturing Technology, 2017; 88(9):3217-32.

[11] F. Ducobu, E. Rivière-Lorphèvre, and E. Filippi, Application of the Coupled Eulerian-Lagrangian (CEL) method to the modeling of orthogonal cutting, European Journal of Mechanics - A/Solids, 2016; 59: 58-66.

[12] E. Uhlmann and E. Barth, Smoothed Particle Hydrodynamics simulation of the machining process of Inconel 718, Procedia Manufacturing, 2018; 18:1-11.

[13] Y. He, J. Zhang, Y. Qi, H. Liu, A. R. Memon, and W. Zhao, Numerical study of microstructural effects on chip formation in high speed cutting of ductile iron with discrete element method, Journal of Materials Processing Technology, 2017; 249:291-301.

[14] E. Uhlmann, R. Gerstenberger, and J. Kuhnert, Cutting Simulation with the Meshfree Finite Pointset Method, Procedia CIRP, 2013: 8:391-96.

[15] J. M. Rodriguez, S. Larsson, J. M. Carbonell, and P. Jonsén, Implicit or explicit time integration schemes in the PFEM modeling of metal cutting processes, Computational Particle Mechanics, 2022; 9(4):709-33.

[16] M. Afrasiabi, H. Klippel, M. Roethlin, and K. Wegener, An improved thermal model for SPH metal cutting simulations on GPU, Applied Mathematical Modelling, 2021; 100:728-50.

[17] M. Afrasiabi, L. Meier, M. Röthlin, H. Klippel, and K. Wegener, GPU-accelerated meshfree simulations for parameter identification of a friction model in metal machining, International Journal of Mechanical Sciences, 2020; 176:105571.

[18] P. J. Arrazola, T. Özel, D. Umbrello, M. Davies, and I. S. Jawahir, Recent advances in modelling of metal machining processes, CIRP Annals - Manufacturing Technology, 2013; 62(2):695-718.

[19] F. Cepero-Mejías, V. A. Phadnis, K. Kerrigan, and J. L. Curiel-Sosa, A finite element assessment of chip formation mechanisms in the machining of CFRP laminates with different fibre orientations, Composite Structures, 2021; 268:113966.

[20] F. Cepero-Mejías, J. L. Curiel-Sosa, K. Kerrigan, and V. A. Phadnis, Study of the machining induced damage in UD-CFRP laminates with various fibre orientations: FE assessment, Procedia CIRP, 2020; 87:366-71.

[21] J. Xu, T. Lin, L. Li, M. Ji, J.P. Davim, N. Geier, M. Chen, Numerical study of interface damage formation mechanisms in machining CFRP/Ti6Al4V stacks under different cutting sequence strategies, Composite Structures, 2022; 285:115236.

[22] Y. Liu, D. Xu, M. Agmell, R. M'Saoubi, A. Ahadi, J.E. Stahl, J. Zhou, Numerical and experimental investigation of tool geometry effect on residual stresses in orthogonal machining of Inconel 718, Simulation Modelling Practice and Theory, 2021; 106:102187.

[23] J. C. Outeiro, J. C. Pina, R. M'Saoubi, F. Pusavec, and I. S. Jawahir, Analysis of residual stresses induced by dry turning of difficult-to-machine materials, CIRP Annals, 2008; 57(1):77-80.

[24] T. Özel and D. Ulutan, Prediction of machining induced residual stresses in turning of titanium and nickel based alloys with experiments and finite element simulations, CIRP Annals, 2012; 61(1):547-50.

[25] F. A. V. da Silva and J. C. Outeiro, Machining simulation of Inconel 718 using Lagrangian and Coupled Eulerian-Lagrangian approaches, Procedia CIRP, 2021; 102:453-58.

[26] G. Ortiz-de-Zarate, A. Sela, A. Madariaga, T. H. C. Childs, and P. J. Arrazola, Sensitivity analysis of the input parameters of a physical based ductile failure model of Ti-6Al-4V for the prediction of surface integrity, Procedia CIRP, 2020; 87: 533-38.

[27] Y. Liu, M. Agmell, D. Xu, A. Ahadi, J.-E. Stahl, and J. Zhou, Numerical contribution to segmented chip effect on residual stress distribution in orthogonal cutting of Inconel718, The International Journal of Advanced Manufacturing Technology, 2020; 109(3): 993-1005.

[28] J. C. Outeiro, D. Umbrello, R. M'Saoubi, and I. S. Jawahir, Evaluation of Present Numerical Models for Predicting Metal Cutting Performance And Residual Stresses, Machining Science and Technology, 2015; 19(2):183-216.

[29] X. Xu, J. Outeiro, J. Zhang, B. Xu, W. Zhao, and V. Astakhov, "Machining simulation of Ti6Al4V using coupled Eulerian-Lagrangian approach and a constitutive model considering the state of stress," Simulation Modelling Practice and Theory, 2021; 110:102312.

[30] S. Imbrogno, S. Rinaldi, D. Umbrello, L. Filice, R. Franchi, and A. Del Prete, A physically based constitutive model for predicting the surface integrity in machining of Waspaloy, Materials & Design, 2018; 152:140-55.

[31] L. A. Denguir, J. C. Outeiro, G. Fromentin, V. Vignal, and R. Besnard, A physical-based constitutive model for surface integrity prediction in machining of OFHC copper, Journal of Materials Processing Technology, 2017; 248:143-60.

[32] M. Dumas, D. Fabre, F. Valiorgue, G. Kermouche, A. Van Robaeys, M. Girinon, A. Brosse, H. Karaouni, J. Rech, 3D numerical modelling of turning-induced residual stresses – A two-scale approach based on equivalent thermo-mechanical loadings, Journal of Materials Processing Technology, 2021; 297:117274.

[33] G. Methon, F. Valiorgue, M. Dumas, A. Van-Robaeys, U. Masciantonio, A. Brosse, H. Karaouni, J. Rech, Development of a 3D hybrid modeling of residual stresses induced by grooving, Procedia CIRP, 2019; 82:400-5.

[34] A. Vovk, J. Sölter, and B. Karpuschewski, Numerical investigation of the influence of multiple loads on material modifications during hard milling, Procedia CIRP, 2021; 102:500-5.

[35] A. Vovk, J. Sölter, and B. Karpuschewski, Finite element simulations of the material loads and residual stresses in milling utilizing the CEL method, Procedia CIRP, 2020; 87:539-544.

[36] K. Zhuang, S. Zhou, L. Zou, L. Lin, Y. Liu, J. Weng, J. Gao, Numerical investigation of sequential cuts residual stress considering tool edge radius in machining of AISI 304 stainless steel, Simulation Modelling Practice and Theory, 2022; 118:102525.

[37] Q. Yue, Y. He, Y. Li, and S. Tian, Investigation on effects of single- and multiple-pass strategies on residual stress in machining Ti-6Al-4V alloy, Journal of Manufacturing Processes, 2022; 77:272-81.

[38] S. Razanica, A. Malakizadi, R. Larsson, S. Cedergren, B.L. Josefson, FE modeling and simulation of machining Alloy 718 based on ductile continuum damage, International Journal of Mechanical Sciences, 2020; 171:105375.

[39] P. Landau, S. Osovski, A. Venkert, V. Gärtnerová, and D. Rittel, The genesis of adiabatic shear bands," Scientific Reports, 2016; 6: 37226.

[40] V. Schulze, F. Bleicher, C. Courbon, M. Gerstenmeyer, L. Meier, J. Philipp, J. Rech, J. Schneider, E. Segebade, A. Steininger and K. Wegener, Determination of constitutive friction laws appropriate for simulation of cutting processes, CIRP Journal of Manufacturing Science and Technology, 2022; 38:139-158.

[41] I.S. Jawahir, H. Attia, D. Biermann, J. Duflou, F. Klocke, D. Meyer, S.T. Newman, F. Pusavec, M. Putz, J. Rech, V. Schulze, Cryogenic manufacturing processes, CIRP Annals , 2016; 65(2): 713-36.

[42] X. Li, E. M. Kopalinsky, and P. L. B. Oxley, A Numerical Method for Determining Temperature Distributions in Machining with Coolant: Part 1: Modelling the Process, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 1995; 209(1): 33-43.

[43] A. Duchosal, S. Werda, R. Serra, R. Leroy, and H. Hamdi, Numerical modeling and experimental measurement of MQL impingement over an insert in a milling tool with inner channels, International Journal of Machine Tools and Manufacture, 2015; 94:37-47.

[44] A. Shokrani, J. Betts, and M. Carnevale, Thermal analysis in MQL end milling operations, Procedia CIRP, 2021; 101:358-61.

[45] A. Shokrani and J. Betts, A new hybrid minimum quantity lubrication system for machining difficult-to-cut materials, CIRP Annals, 2020; 69(1):73-76.

[46] E. Tahmasebi, P. Albertelli, T. Lucchini, M. Monno, and V. Mussi, "CFD and experimental analysis of the coolant flow in cryogenic milling,"

International Journal of Machine Tools and Manufacture, vol. 140, pp. 20-33, 2019.

[47] C. Salame and R. Bejjani, A better understanding of the cryogenic environment and the effect of nozzle location on the machinability of low carbon steel, Journal of Manufacturing Processes, 2022; 74: 544-56.

[48] E. Oezkaya, N. Beer, and D. Biermann, Experimental studies and CFD simulation of the internal cooling conditions when drilling Inconel 718, International Journal of Machine Tools and Manufacture, 2016; 108: 52-65.

[49] I. Iovkov, M. Bücker, and D. Biermann, A modified tool design for the drilling of high-performance aerospace materials, CIRP Annals, 2021; 70(1): 83-6.

[50] P. G. Benardos and G. C. Vosniakos, Predicting surface roughness in machining: a review, International Journal of Machine Tools and Manufacture, 2003; 43(8): 833-44.

[51] A. Meijer, J. A. Bergmann, E. Krebs, D. Biermann, and P. Wiederkehr, Analytical and Simulation-Based Prediction of Surface Roughness for Micromilling Hardened HSS, Journal of Manufacturing and Materials Processing, 2019; 3(3):70.

[52] F. Ismail, M. A. Elbestawi, R. Du, and K. Urbasik, Generation of Milled Surfaces Including Tool Dynamics and Wear, Journal of Engineering for Industry, 1993; 115(3): 245-52.

[53] D. Montgomery and Y. Altintas, Mechanism of Cutting Force and Surface Generation in Dynamic Milling, Journal of Engineering for Industry, 1991; 113(2); 160-68.

[54] J. Niu, J. Jia, Y. Sun, and D. Guo, Generation Mechanism and Quality of Milling Surface Profile for Variable Pitch Tools Considering Runout, Journal of Manufacturing Science and Engineering, 2020; 142(12).

[55] Y. Zhuo, Z. Han, D. An, and H. Jin, Surface topography prediction in peripheral milling of thin-walled parts considering cutting vibration and material removal effect, International Journal of Mechanical Sciences, 2021; 211: 106797.

[56] T. Insperger and G. Stépán, Semi‐discretization method for delayed systems, International Journal for numerical methods in engineering, 2002: 55(5): 503-518.

[57] Z. M. Kilic and Y. Altintas, Generalized mechanics and dynamics of metal cutting operations for unified simulations, International Journal of Machine Tools and Manufacture, 2016: 104: 1-13.

[58] C. L. He, W. J. Zong, and J. J. Zhang, Influencing factors and theoretical modeling methods of surface roughness in turning process: State-of-the-art, International Journal of Machine Tools and Manufacture, 2018; 129: 15-26.

[59] S. Seguy, G. Dessein, and L. Arnaud, Surface roughness variation of thin wall milling, related to modal interactions, International Journal of Machine Tools and Manufacture, 2008; 48(3): 261-74.

[60] S. Zhenyu, L. Luning, and L. Zhanqiang, Influence of dynamic effects on surface roughness for face milling process, The International Journal of Advanced Manufacturing Technology, 2015; 80(9):1823-31.

[61] B. Yan, Y. Hao, L. Zhu, and C. Liu, Towards high milling accuracy of turbine blades: A review, Mechanical Systems and Signal Processing, 2020; 170:108727.

[62] G. Chen, Y. Zou, X. Qin, J. Liu, Q. Feng, and C. Ren, Geometrical texture and surface integrity in helical milling and ultrasonic vibration helical milling of Ti-6Al-4V alloy, Journal of Materials Processing Technology, 2020; 278: 116494.

[63] G. Chen, C. Ren, Y. Zou, X. Qin, L. Lu, and S. Li, Mechanism for material removal in ultrasonic vibration helical milling of Ti6Al4V alloy, International Journal of Machine Tools and Manufacture, 2019, 138: 1-13.

[64] V. Chomienne, F. Valiorgue, J. Rech, and C. Verdu, Influence of Part's Stiffness on Surface Integrity Induced by a Finish Turning Operation of a 15-5PH Stainless Steel, Procedia CIRP, 2016; 45: 19-22.

[65] X.-D. Huang, X.-M. Zhang, J. Leopold, and H. Ding, Analytical Model for Prediction of Residual Stress in Dynamic Orthogonal Cutting Process, Journal of Manufacturing Science and Engineering, 2017; 140(1).

[66] Y. Kamada and H. Sasahara, Residual stress fluctuates periodically via the workpiece rotation phase during low frequency vibration cutting, Precision Engineering, 2021; 72:583-94.

[67] J. C. Outeiro, J. P. Costes, and J. R. Kornmeier, Cyclic Variation of Residual Stress Induced by Tool Vibration in Machining Operations, Procedia CIRP, 2013; 8:493-7.

[68] A. Maurotto and L. T. Tunc, Effects of Chattering on Surface Integrity in Robotic Milling of Alloy 690, ASME Pressure Vessels and Piping Conference, 2017: 6A.

[69] S. C. Lin and M. F. Chang, A study on the effects of vibrations on the surface finish using a surface topography simulation model for turning, International Journal of Machine Tools and Manufacture, 1998; 38(7): 763-82.

[70] L. Colantonio, L. Equeter, P. Dehombreux, and F. Ducobu, A Systematic Literature Review of Cutting Tool Wear Monitoring in Turning by Using Artificial Intelligence Techniques, Machines, 2021; 9(12): 351.

[71] A. B. Khoshaim, A. H. Elsheikh, E. B. Moustafa, M. Basha, and A. O. Mosleh, Prediction of residual stresses in turning of pure iron using artificial intelligence-based methods, Journal of Materials Research and Technology, 2021; 11: 2181-94.

[72] Y. Karpat and T. Özel, Multi-objective optimization for turning processes using neural network modeling and dynamic-neighborhood particle swarm optimization, The International Journal of Advanced Manufacturing Technology, 2007; 35(3): 234-47.

[73] A. Kosarac, C. Mladjenovic, M. Zeljkovic, S. Tabakovic, and M. Knezev, Neural-Network-Based Approaches for Optimization of Machining Parameters Using Small Dataset, Materials, 2022; 15(3): 700.

[74] F. J. Pontes, J. R. Ferreira, M. B. Silva, A. P. Paiva, and P. P. Balestrassi, Artificial neural networks for machining processes surface roughness modeling, The International Journal of Advanced Manufacturing Technology, 2010; 49(9): 879-902.

[75] R. Azouzi and M. Guillot, On-line prediction of surface finish and dimensional deviation in turning using neural network based sensor fusion, International Journal of Machine Tools and Manufacture, 1997; 37(9): 1201-17.

[76] M. P. Motta, C. Pelaingre, A. Delamézière, L. B. Ayed, and C. Barlier, Machine learning models for surface roughness monitoring in machining operations, Procedia CIRP, 2022; 108:710-15.

[77] H. C. Möhring, S. Eschelbacher, and P. Georgi, Machine learning approaches for real-time monitoring and evaluation of surface roughness using a sensory milling tool, Procedia CIRP, 2021; 102: 264-69.

[78] W.-J. Lin, S.-H. Lo, H.-T. Young, and C.-L. Hung, Evaluation of deep learning neural networks for surface roughness prediction using vibration signal analysis, Applied Sciences, 2019; 9(7):1462.

[79] N. Fang and P. S. Pai, A new computational intelligence approach to predicting the machined surface roughness in metal machining, International Journal of Machine Learning and Computing, 2018; 8:524.

[80] Z. Wang et al., Acoustic Emission Characterization of Natural Fiber Reinforced Plastic Composite Machining Using a Random Forest Machine Learning Model, Journal of Manufacturing Science and Engineering, 2020; 142(3).

[81] D. Knittel, H. Makich, and M. Nouari, Milling diagnosis using artificial intelligence approaches, Mechanics & Industry, 2019; 20: 809.

[82] D.-M. Tsai, J.-J. Chen, and J.-F. Chen, A vision system for surface roughness assessment using neural networks, The International Journal of Advanced Manufacturing Technology; 1998, 14: 412-22.

[83] A. P. Rifai, H. Aoyama, N. H. Tho, S. Z. Md Dawal, and N. A. Masruroh, Evaluation of turned and milled surfaces roughness using convolutional neural network, Measurement, 2020; 161: 107860.

[84] M. Liu, C. Fai Cheung, N. Senin, S. Wang, R. Su, and R. Leach, On-machine surface defect detection using light scattering and deep learning, Journal of the Optical Society of America A, 2020; 37: 53-9.

[85] B. Bhandari and G. Park, Noncontact Surface Roughness Evaluation of Milling Surface Using CNN-Deep Learning Models; 2021.

[86] J. Schoop, H. A. Poonawala, D. Adeniji, and B. Clark, AI-enabled dynamic finish machining optimization for sustained surface integrity, Manufacturing Letters, 2021; 29: 42-6.