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AI-based optimisation of total machining performance: A review

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ABSTRACT

Advanced modelling and optimisation techniques have been widely used in recent years to enable intelligent manufacturing and digitalisation of manufacturing processes. In this context, the integration of artificial intelligence in machining provides a great opportunity to enhance the efficiency of operations and the quality of produced components. Machine learning methods have already been applied to optimise various individual objectives concerning process characteristics, tool wear, or product quality in machining. However, the overall improvement of the machining process requires multi-objective optimisation approaches, which are rarely considered and implemented. The state-of-the-art in application of various optimisation and artificial intelligence methods for process optimisation in machining operations, including milling, turning, drilling, and grinding, is presented in this paper. The Milling process and deep learning are found to be the most widely researched operation and implemented machine learning technique, respectively. The surface roughness turns out to be the most critical quality measure considered. The different optimisation targets in artificial intelligence applications are elaborated and analysed to highlight the need for a holistic approach that covers all critical aspects of the machining operations. As a result, the key factors for a successful total machining performance improvement are identified and discussed in this paper. The AI methods were investigated and analysed in the frame of the IMPACT project initiated by the CIRP.

1. Introduction to artificial intelligence in machining

The immense increase of computational power, data storage capacity, and transmission rates together with access to large volumes of data from a variety of sources provide the basis for the successful implementation of artificial intelligence (AI) technology in a broad spectrum of application areas. AI has become a key player in support and improvement of many everyday life activities and challenges, such as navigation, procuring, medical treatment, information management, and communication. It is also an important part of Industry 4.0 which denotes the digitalisation and automation efforts in manufacturing [1, 2]. Machining, as one of the key secondary operations to generate functional surfaces, has attracted much attention and already benefited from AI, machine learning (ML), and optimisation since the rapid technological advancement in information processing technology has facilitated their application [3,4]. Predictive models based on ML algorithms have been implemented to monitor, regulate, and enhance the resource and cost efficiency of various machining processes to ensure produced parts of high quality.

1.1. AI technologies in machining

AI applications in machining, according to the published literature so far, are mostly focused on using a single evaluation criterion, such as surface roughness [5–7] or tool wear [8–10], for process assessment and optimisation. This is even though machining is a very complex operation covering several processes defined by the interaction between machine tool, environment, and workpiece. Considering machining as a system of cutting tool, machine tool, and work material, the total machining performance (TMP) [11] must be evaluated by several criteria, including

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surface finish, tool wear rate, tool geometry, dimensional and geometrical accuracy, cutting power, and chip breakability. Therefore, a comprehensive approach to assess and improve the TMP should not only include process outputs such as cutting forces or tool wear, but also the quality of produced parts, environmental factors, and production costs to maximise the functional performance and the process sustainability via multi-objective optimisation techniques.

Various modelling techniques including analytical, numerical, empirical, or physics-based methods [4,7,12–16] as well as data-based techniques, such as fuzzy logic and artificial neural networks (ANN), can be used to model process-related targets as a precondition for single- and multi-objective optimisation. However, in the last decade data-based algorithms from AI, such as ML and evolutionary optimisation algorithms, have rapidly become an important element of such models to enhance the machining performance and to enable a smart and sustainable manufacturing process [3,17,18].

A considerable number of review papers have already been published in recent years covering various constituents of AI-based process optimisation in machining from general performance assessment measures and optimisation targets over typical data sources, up to ML and optimisation algorithms (see Fig. 1). These delve into general discussions on the successful integration of AI in manufacturing or machining [15,19–23] and special considerations on selected machining operations including laser beam machining [24], abrasive finishing [25], drilling [26,27], or milling [28]. Additionally, application of particular modelling targets with respect to the ML approach and optimisation potential, for example, rate of penetration in drilling [4], surface roughness [29], cutting forces [16], and tool breakage [30], were analysed. Finally, deep learning for tool condition monitoring [31] or evolutionary techniques for machining [32] highlight the particular value of data-based algorithms for manufacturing processes.

1.2. Optimisation in machining

Extensive research has been conducted over the past decades on the development and application of optimisation algorithms to enhance machining performance and process monitoring. However, with the continuous advancement of algorithms and the rapid progress in information technologies, there is an urgent need to further develop optimisation methods in machining to fully harness the potential benefits of data-driven methods. The conventional machining performance assessment methods are not very efficient for the evaluation of the TMP due to the large number of variables involved. Therefore, a series of fuzzy-set mathematical models have been developed and implemented to address this shortcoming [11]. However, the performance of these models is bound to the available algorithms and information technologies present at the time. Therefore, using the modern data-based toolbox of AI including the methods can significantly enhance the performance of these models with respect to both effectiveness and accuracy.

1.3. Machine learning in machining

ML applications in manufacturing processes have gathered significant interest among researchers. The existing literature covers either summaries of ML applications in different operations [3,33] or discusses specific case studies, such as tool wear or surface quality of the machined parts [34]. Process outputs such as cutting forces and surface roughness are reportedly predicted using ANNs [35], while sensor fusion [36] and fuzzy optimisation [37] have been investigated to establish a reliable measurement setup for a high-quality data acquisition that is crucial for optimisation tasks. A review of literature from the late 20th century about the identification of optimal machining parameters primarily using AI methods has been provided in [38]. This review highlights the fact that only a limited number of studies have utilised a combined approach involving both ML methods and optimisation algorithms as presented in [39,40]. Furthermore, evolutionary and, in particular, genetic algorithms [12,41–45] were used and evaluated to achieve an optimal manufacturing process. Optimisation techniques such as particle swarm optimisation [46], response surface methodology [47], weighted grey relational analysis [48,49], or the NSGA-II algorithm for single- and multi-view optimisation [50] have also been implemented in the field of machining.

1.4. Paper structure

Starting from recent work on advanced machining in [3] and considering the exponential development and application of data-based modelling, the present paper is focused on the *state-of-the-art since 2018* with particular emphasis on the improvement of the machining process by integrating ML modelling and data-based optimisation. The paper

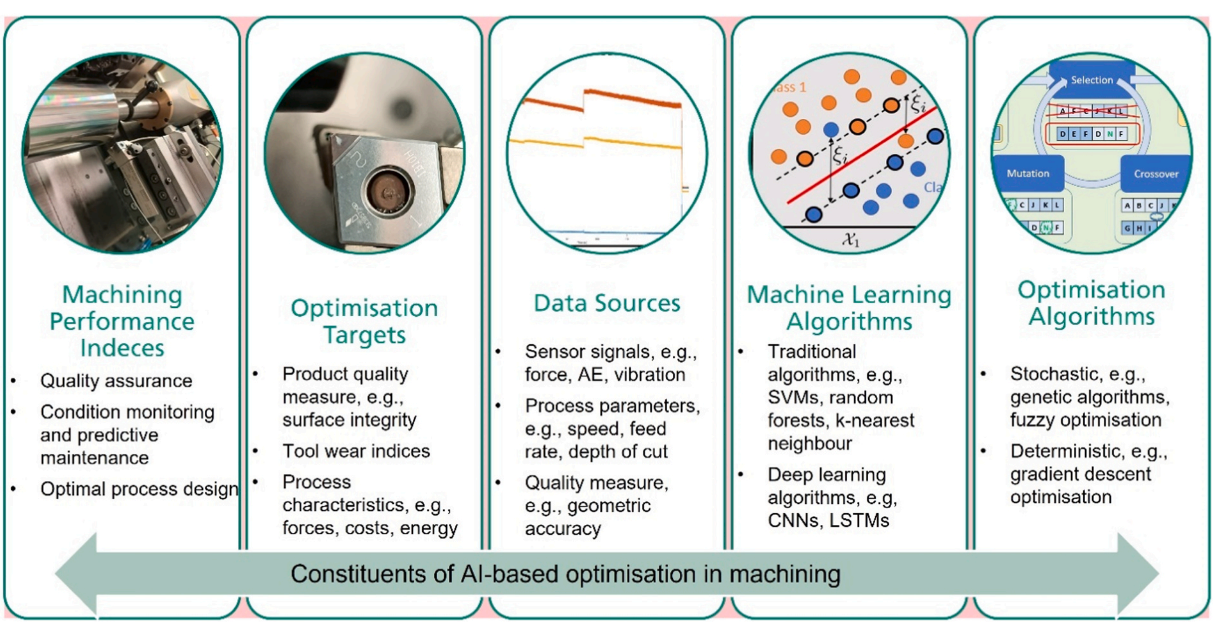

Fig. 1. AI-based optimisation in machining includes the identification of performance indices, the selection of optimisation targets and data sources, as well as the choice of ML and optimisation algorithms.

delivers a thorough analysis and systematic presentation of process parameters and variables as data sources as well as the modelling targets process characteristics, tool wear, and workpiece quality. The importance of multi-objective optimisation for TMP improvement as well as challenges and preconditions for the successful implementation are discussed extensively.

A brief introduction to machining operations in Section 2 is followed by a brief description of ML and data-based optimisation algorithms applied to the field of machining science. Typical data sources and associated preprocessing, as well as feature extraction methods required for high-quality modelling and prediction of machining operations are discussed in Section 4. The review of the state-of-the-art in ML applications to machining in Section 5 provides a critical assessment of ML approaches as a precondition for data-based optimisation. Additionally, the most relevant modelling targets together with available information sources used as input and output data of the models are presented in detail in Section 5. Preconditions and obstacles for the implementation of AI and ML towards TMP optimisation are discussed in Section 6 and a strategy is proposed for a successful TMP assessment and optimisation. Finally, the concluding remarks are described in Section 7.

2. The machining process

Machining processes remain among the most frequently used operations to generate functional surfaces for applications in various sectors including aerospace, automotive, and energy. Cutting is generally defined as a form-shaping machining process via chip removal due to an interaction between a workpiece and a tool. Hence, it is commonly referred to as subtractive manufacturing to be easily differentiated from additive manufacturing [51]. Machining processes are often categorised into conventional and non-conventional operations depending on the source of energy used to remove the material [32,52]. The conventional operations are based on a relative motion between the tool and the work material, defined by the kinematics of the process, which results in the mechanical chip formation. The operations are divided into cutting (e.g., turning, drilling, milling) and abrasive processes (e.g., grinding, lapping, polishing) based on the number of defined geometrical features of the cutting edges. The shapes of the cutting edges are known and can be quantified in the cutting operations, while the features of the cutting edges can only be described statistically in the abrasive processes [53]. Process parameters (i.e., cutting speed, feed, and depth of cut), tool properties (e.g., size, coating, edge properties) and the cooling strategy (e.g., flood, minimum quantity lubrication, cryogenic) as well as the workpiece material are among the critical factors required to design a cutting process.

The workpiece quality is often predetermined by technical specifications defining surface characteristics, and dimensional accuracy [29]. However, the produced surface integrity, which has an impact on the functional performance of the parts, is characterised by mechanical and metallurgical properties within the surface layer, including residual stresses, microhardness, or the grain structure [54]. Therefore, an optimised cutting process will positively affect the quality of the generated surfaces [52,55] as well as improve the sustainability of the machining process with respect to emissions and energy consumption [47,56].

3. Fundamentals of machine learning and optimisation

In Section 3.1 necessary terms and concepts from ML theory, including a categorisation of algorithms and learning tasks, are presented. It is followed by an introduction of ML and optimisation algorithms most frequently applied in the field of machining.

3.1. Terms and learning tasks

The terms artificial intelligence (AI), machine learning (ML), and deep learning (DL) are often used interchangeably and cannot be distinguished clearly in the literature, despite being different concepts with a decreasing level of generalisation. AI refers to the intelligent performance of machines [57,58] enabled through the entirety of algorithms, software, and hardware and, hence, covers the broadest scope. According to [59], AI is the ability of a system to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through their flexible adaptation [60]. Whereas, ML refers to the mathematical algorithms which draw conclusions from data in the form of predictions, i.e., automatically transform experience into knowledge [61]. In this sense, optimisation algorithms are both an integral part of AI and are applied to find optimal prediction models from ML to solve present learning problems. DL as a subgroup of ML refers to the application of artificial neural networks (ANNs) with hidden layers (Section 3.2). Therefore, the ML branches of ANNs and DL can be regarded practically the same. Modern ANNs are able to autonomously learn the representative features of data which are needed to solve ambitious learning tasks [62,63]. This specific capability of ANNs combined with the increased computing power, storage capacity, and data emergence in recent years has led to astonishing results, for example in object detection or speech recognition, however, at the expense of a limited explainability of the corresponding algorithms [64].

An ML model is a function f which assigns an appropriate output or label $y \in \mathscr{Y}$ to every instance x of an input space $\mathscr{X}$ (Fig. 2). The input x is an appropriate feature representation of the instance, e.g., an image, or a sensor measurement and labels are for example real values, classes, or rankings of data sets. If more than one feature sets for the instances are available, so-called multi-view learning techniques can be applied [65]. A predefined training data set is used to generate the predictor function using an ML algorithm in the training phase, while the performance of a model is evaluated in the testing phase with an independent test dataset together with a convenient performance measure. Supervised, unsupervised, and reinforcement learning (RL) are the three learning paradigms of ML. Supervised learning refers to scenarios where labelled examples, i.e., pairs (x, y) from $\mathscr{X} \times \mathscr{Y}$, are available for training with the goal of optimally aligning true labels and predicted labels in a way that is determined by the algorithm. Regression, the prediction of a real-number, or classification, the prediction of two or more predefined classes, are typical tasks for supervised learning.

In contrast, in an unsupervised setting only unlabelled instances, i.e., elements of $\mathscr{X}$, are available for training. Clustering and dimensionality reductions are important examples of unsupervised learning tasks. These refer to an optimal grouping of instances and or reducing the input dimension with a minimal loss of information, respectively. RL describes learning by trial and error, e.g., in playing a game or optimising operations in a production process, whereby a programme or an agent operates in an environment and aims at maximising its success measured in form of cumulative rewards for a sequence of actions [58,60,66]. Independent of learning task or paradigm, transfer learning (TL) is an ML approach [67] which intends to transfer knowledge from the

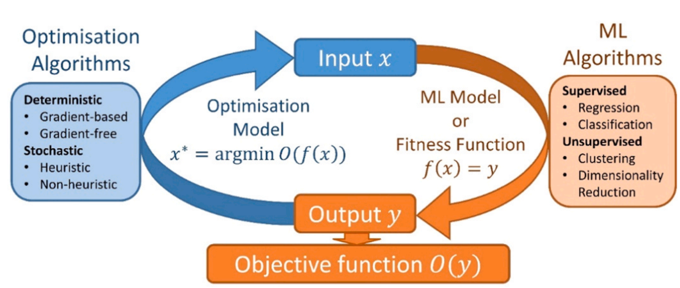

Fig. 2. The relation between process input $\boldsymbol{x}$ and output $\boldsymbol{y}$ can be captured with an ML model or a fitness function and the optimisation model can be used to determine the most suitable input $\boldsymbol{x}^*$ which minimises the objective function.

solution of one learning task to another related task, e.g., by modifying an existing ML model to a similar problem and improving training data set [68].

3.2. Machine learning algorithms

ML models are generated to tackle a specified learning problem from practice by inferring the underlying functional relationship between input and output of a process. A prior analytical relationship between input and output quantities is not needed to build an ML model, however, expert knowledge can be greatly beneficial. The performance of models for a given dataset depends on the used ML algorithm and evaluation measures during training and testing. The majority of ML algorithms applied in machining-related research in the reviewed literature can be grouped in (1.) support vector machines (SVMs), (2.) artificial neural networks (ANNs), (3.) decision tree (DT) algorithms, and (4.) regression analysis (RA).

3.2.1. Support vector machines and kernel methods

SVMs are linear models arising from a regularised risk minimisation approach with beneficial properties of the corresponding loss function, originally with the aim to solve supervised classification or regression problems in high-dimensional features spaces [69,70]. The main objective of support vector classification (SVC) is to find a hyperplane, i.e., a decision boundary, that separates different classes in the inputs such that the margin between instances and the hyperplane is maximal [71]. Additionally, support vector regression (SVR) was developed for regression problems where the optimal hyperplane is determined to best fit the training data points [72]. SVMs can be transformed into so-called kernel methods [73–76] where a symmetric kernel function is used to implicitly map the learning instances from the original feature space to another feature space to enable the solution of a non-linear problem with a linear model. Apart from classification or regression, SVM variations can also be used to tackle other learning problems, such as outlier detection, clustering, or multi-class classification.

3.2.2. Artificial neural networks

ANNs are learning algorithms which minimise the expected risk for future predictions with a model inspired by neural networks in biological organisms [77,78]. An ANN is a connected directional network of nodes (or neurons) organised in multiple layers or complex structural units, such as convolution layers in convolutional neural networks (CNNs) [79]. A variety of input data formats, including image, tabular, or vectorial data can be processed by ANNs to solve different learning tasks. The neurons form the elementary functional units of the network and receive signals in form of edge weights from preceding neurons, process the signal, and pass it on to the subsequent neurons. Specific non-linear activation functions imply a characteristic sensitivity of the neurons and supply ANNs with the capacity to approximate any functional relationship with arbitrary exactness. In contrast to feedforward connections, in recurrent neural networks (RNNs) the nodes' outputs can affect the input of preceding layers by forming a loop, which make RNNs capable of predicting data sequence, e.g., via long-short term memory networks (LSTM). The perceptron algorithm displays the basic functionality of the ANN learning procedure. It implements the successive adaption of the edge weights to the training inputs via back-propagation (BP). The multi-layer perceptron (MLP) is its generalisation with hidden layers. Mostly commonly, the gradient descent optimisation algorithm is utilised for the weight adjustment. The explainability and interpretability of ANNs are typically not obvious because of the non-linearity of the activations, the non-convexity of the corresponding optimisation problem during training, and a typically large number of parameters.

3.2.3. Decision tree learning

A decision tree (DT) is a supervised learning model where leaves are associated with labels and branches correspond to decisions that lead to those labels. At a tree branching the data instances are split according to their feature attributes or thresholds on the feature values. As it is computationally difficult to calculate the optimal tree, DT algorithms are greedy and achieve good results with locally optimal decisions. To this aim, DT learning starts with the root node and successively grows the tree deciding which data attribute (feature) to use for the splitting of the data subset in each node [60]. Gain measures are used to assess the efficiency of decisions based on to what extent they enhance the purity of labels in subsequent leaf nodes and, hence, improves the overall predictive performance of the model. DT models are well-known for their high degree of explainability and interpretability and although they have been developed to solve multi-class classification tasks with discrete-valued attributes, with slight modifications, they can also be used to solve regression tasks as well. These are originally developed to. The random forest algorithm (RF) [80] is an ensemble approach using DTs as well as the principles of bagging training data and subsampling representing features.

3.2.4. Regression analysis

Regression analysis establishes a mathematical model for the statistical relationship of a real-valued dependent variable on one or more independent variables for prediction purposes or causality analysis [81]. Multi-linear regression (MLR) assumes a linear dependency on several input variables, whereas polynomial regression (PR) models the dependent variable as a linear combination of the powers of input variables up to a certain polynomial degree. The method of least squares (LS) regression minimises the empirical risk for an MLR problem with a squared loss function that can be solved as a closed formula under specific conditions. Non-parametric regression is conceptually different, as the prediction function does not assess a fixed parameterisation of a prescribed functional form. Gaussian process regression (GPR) as one representative uses Bayes' theorem to find probability distributions over possible models based on the available dataset.

3.2.5. Other machine learning modelling approaches

Instance-based and generative models from supervised learning have also been used occasionally to predict machining parameters. Instance-based learning does not generate an explicit prediction model but uses the available training data directly for a prediction [60]. The k-nearest neighbour (kNN) algorithm, for example, determines the label of new instances according to the labels of the k closest data points. Generative models, such as Bayesian belief networks [27], take the probability distribution of input and output variables into account for their prediction. Clustering, dimensionality reduction, and outlier detection are important applications of unsupervised learning. Clustering is the attempt to group data points according to their similarity without the awareness of labels. Dimensionality reduction intends to reduce the feature space dimension, for example, via principal component analysis (PCA). Outlier detection aims at finding anomalies which significantly differ from the remaining data.

3.3. Optimisation algorithms

Optimisation, ML, and AI are closely linked with the notions of reasoning and decision making [19,26,82–84] which primarily relate to human attributes. The optimisation aims to maximise or minimise an output or objective function O by calculating the most appropriate input x^* (Fig. 2). The machining process output y can sometimes be measured or calculated directly from the input y and covered with a fitness function (compare genetic algorithms in Section 3.3.1). Examples of such outputs are the measured energy or the calculated production costs. In the other case, ML algorithms can be employed to capture the underlying patterns and correlations from data samples of input x and output y. Given specified input values, the aim of single-objective optimisation (SOO) is to optimise one objective function with respect to the inputs. In contrast, multi-objective optimisation (MOO) denotes the simultaneous consideration of various objective functions and aims to fulfil all targets to their greatest extent [27]. Depending on the preconditions of the optimisation problem, many strategies with corresponding solution have been developed that involve the calculation of Hessians, gradients, or values of the focused objective function in different manners. For example, the minimisation of a linear least squares problem can be calculated as closed formula whereas Newton's method is an iterative procedure [88]. The optimisation approaches can be broadly grouped as deterministic or stochastic algorithms [89–91] based on their characteristics.

In addition to the improvement of the machining process per se, optimisation is also used to find the best hyperparameters [8,13,24,85,86], feature representation, or ML pipeline [87] during training. Furthermore, optimisation is utilised to determine the best predictor function out of a set of candidates, for example, via sequential minimal optimisation (SMO) for SVMs [74] or stochastic gradient descent for ANNs [6].

In recent years, the application of data-based optimisation heuristics for machining processes are being used to an increasing extent along with the expansion of AI technology. The most frequently applied data-based optimisation algorithms in machining are briefly discussed in the following sections. Precise applications are presented in Section 5.

3.3.1. Biology-inspired algorithms

Algorithms inspired by biology mimic natural processes for optimisation and improvement [17]. Genetic algorithms (GA), genetic programming (GP), and particle swarm optimisation (PSO) are prominent representatives of evolutionary algorithms. A subset of domain instances (population of individuals) is considered in a GA [60,92], i.e., chromosomes of genes, in a way to satisfy predefined descriptions of individual features. The instances run through a cycle of mutation (random exchange of genes) and crossover (exchange of chromosome parts between instances) for the generation of new instances. A fitness function is used to select the most appropriate individuals to enter the next round of the cycle. Although most of the conventional GA algorithms target SOO problems, MOO can also be addressed directly using non-dominated sorting genetic algorithm II (NSGA-II) [93,94]. GPs [28,87] follow the principles of evolution as well, but their optimisation instances are subsequent calculation or preprocessing units called programmes whose number is not predetermined, unlike the number of genes in GAs. In a PSO [28] a population of individuals (swarm of particles) is moving around in the search space in order to find optimal points with respect to a fitness function. The particles can move either in random directions (similar to the mutation step) or according to the movement of the entire swarm, i.e., depending on other particles (similar to the crossover step). The flower pollination algorithm (FPA) is another bio-inspired optimisation approach imitating the natural flower pollination process [95,96]. The FPA stochastically combines aspects of abiotic self-pollination (local) and biotic cross-pollination (global) using random parameters and information of both the considered individuals (flowers) and the remaining population. The navigation behaviour of birds flying in various groups in search of food has inspired the development of the pigeon optimisation algorithm (POA) [97] which can be applied for shortest paths problems in a given population of individuals (paths).

3.3.2. Fuzzy optimisation

Fuzzy optimisation or fuzzy programming refers to optimisation approaches under uncertainty conditions, i.e., where data is imprecise or fuzzy [84]. Often neither the exact values of variables are known nor a high-precision outcome is necessary to achieve an acceptable optimisation result [98]. A fuzzy set is characterised by its membership function that indicates for each element the probability of its membership to the respective set. Similar to classical set theory, operations such as union, intersection, and complement can also be defined for fuzzy sets in order to formalise fuzzy logic and to allow for conclusions from uncertain or incomplete information [84]. Fuzzy logic can also be applied in process control especially when dealing with input variables that exhibit instability or fluctuations [26]. The values of fuzzy variables can be included in quantitative prediction models and optimisation via membership functions or probability distributions [11,98–100]. A special case is fuzzy clustering, where the assignment of a data object to a cluster is not deterministic but fuzzy in the sense of a membership function [28]. Fuzzy inference systems (FIS) combine a prediction model and membership functions as well as fuzzy rules (fuzzy logic) to draw conclusions [24,101,102]. Consequently, neuro-fuzzy inference system (NFIS) or fuzzy neural networks apply ANNs as prediction model (ANFIS).

3.3.3. Further optimisation algorithms

Bayesian optimisation (BO), spiral dynamic algorithm (SDA), and the Levenberg-Marquardt algorithm (LMA) are also among the methods applied to optimisation in machining. BO is used to globally optimise an unknown objective or a function expensive to evaluate by treating it as a random function and iteratively updating an objective function until an optimum is reached [103,104]. Similar to biology-inspired algorithms, the SDA is motivated by spiral phenomena appearing in nature and aims at a global optimum via diversification and intensification strategies [105]. The LMA is used to solve non-linear least squares problems [106].

4. Data acquisition and preprocessing

Process parameters are defined physical quantities that describe a machining process and can take different values to represent various operational conditions. Hence, process parameters are targets for process optimisation. In contrast, process variables are continuously monitored during an operation to assess the machining performance. The process variables include all measurable signals, such as forces, temperature, or properties that can be observed while the process is running. Therefore, they cannot be adjusted or calibrated directly. This section reports on applied process parameters and measured process variables with respect to data content, recording, and preparation in the context of TMP optimisation.

4.1. Process parameters and process variables

The cutting conditions including cutting speed, depth of cut, and feed rate very often appear as considered adjustable parameters in AI models. Other factors such as lubrication, cooling strategies, cutting tool properties, such as geometry or coating, and machining tool can also be varied to some extent to achieve an optimised machining performance. Both process parameters and variables are used as model input for ML prediction models. Process variables as well as process characteristics like tool and product properties appear typically as ML model outputs. The three most frequent modelling scenarios are shown in Fig. 3.

A large variety of sensor types have been used in different AI approaches to improve the TMP. Examples are reported in Table 1. The inclusion of acoustic [10,99,107–110], acceleration or vibration [111,112], force or torque [8,113,114], and displacement sensors [100] is already well-established and has been studied intensively in the field of machining. Their extensive application can be explained with the relative ease of assembly, data capture, and analysis compared to other signals, such as machining-induced temperature from thermocouples [115] or thermal imaging [116]. Despite technical difficulties involved in temperature measurements, it is reported that high-speed and thermal imaging combined with modern image processing technologies provides a wealth of information about machining systems that can support the development of relevant DL techniques [117].

In general, it is desirable to obtain information from multiple sensors to investigate and exploit the potentials of sensor fusion [118]. The simultaneous evaluation and combination of several sensors through

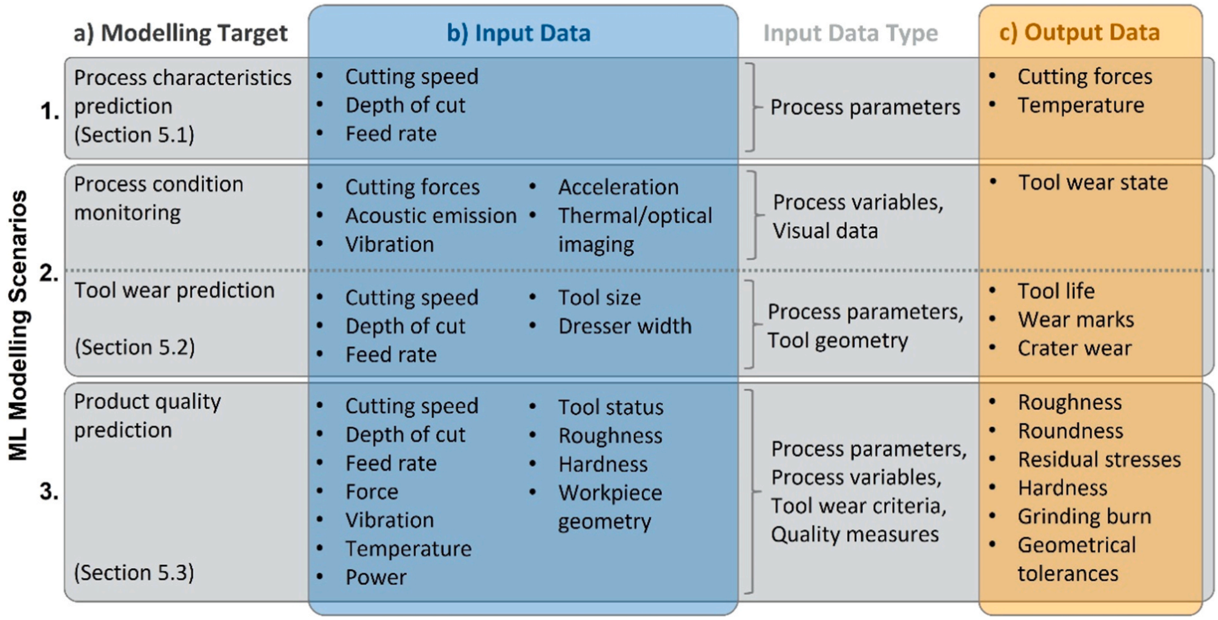

Fig. 3. The three typical ML modelling scenarios in machining with their associated (a) modelling targets, (b) input data, and (c) and output data.

Table 1
Important configurations of data acquisition, preprocessing, and feature extraction in ML applications for prediction and optimisation of different modelling targets in machining.

Data source	Reference	Data acquisition	Preprocessing and feature extraction	Modelling target
Acoustic emission (AE)	[124]	Piezoelectric AE sensor on the workpiece with grease as acoustic bond (40MSPS) -> data acquisition card -> voltage-time-signal -> computer -> AE software	Amplified and high passed filtered to only observe continuous interaction, AE-RMS as input, tool wear as output of a neural network	Tool wear
	[99]	AE sensor on dresser holder -> Amplifier module -> oscilloscope with 2 MHz sampling rate -> PC for storage and digital signal processing	Ratio of power (ROP) from 25-40 kHz band, mean and standard deviation values of ROP, fuzzy systems	Grinding wheel wear
Cutting force and torque	[125]	Kistler 9255B dynamometer ->TEAC DR-FI data recorder	Force, feed rate, eccentricity of face cutting and workpiece geometry, neural network	Average cutting force
	[100]	Dynamometer: force and torque; feed rate, spindle speed and drill parameter manually recorded	Delamination, thrust force and torque, normalised data	Delamination, thrust force and torque
	[114]	Kistler 9257 A dynamometer -> Kistler 5011 signal amplifier -> data acquisition system in Labview	Transformation of the signals to numerical format -> data cleaning -> split into training and validation data	Cutting force
Vibration	[126]	Endevco 165 3-axis accelerometer to spindle housing and Kistler 8141 A accelerometer on workpiece	Sampling and FFT -> feature selection -> band pass filtering -> backpropagation neural network	Class of tool wear
Merged signals from sensor fusion	[127]	Dynamometer & accelerometer combined -> amplifier -> data acquisition system DAP 2400/e6 -> PC	Sampling, new features by combining signals and their statistical values through addition, multiplication, and division	Tool wear
	[112]	Dynamometer & accelerometer combined -> amplifier -> data acquisition system from national instruments -> TDMS file	Feature generation from the power spectral density of the segmented raw signals -> feature selection	Roughness, profile deviation, roundness
Vision system	[117]	Optical imaging of the machined surface	Feature extraction, SVR to find relation between surface features and tool wear	Tool flank wear
Motor current and power	[122]	Edge device, recording machine data with 500 Hz	Data cleaning and sampling, classification model (defective tool or not) and regression model (tool wear)	Tool condition monitoring, tool defect detection
	[128]	Feedback sensors to record the main drive power	Maximum, and minimum value at beginning, middle and end of the operation, data averaging	Flatness deviation

multi-view learning is reported to reveal correlations between input and output data that would not be available using a single signal [65]. A retrofit of machines with additional sensor equipment complicates both the experimental setup and the data analysis, for what reason it is preferable to use information from already embedded sensors in machine tools or obtained from the respective control unit. These can be extracted using hardware or software solutions, e.g., edge devices or gateways, and streaming the data directly to an Internet of Things (IoT) platform, databases, or a PC [119]. However, the potential intrinsic redundancy of information is generally lower when only few signals or features are used [19]. Feature extraction techniques can be applied to determine the degree of redundancy and to extract the most relevant features or data representations of the recorded signals (Section 4.3).

4.2. Data acquisition and storage

The acquisition of sufficient data of adequate quality is generally an essential part of ML approaches. For machining problems, the pipeline for acquisition, storage, and data transfer depends on the conditions and associated environment. Table 1 summarises the most important measurement setups, including signals and associated data acquisition systems used to obtain required input and output data for ML approaches in machining with different optimisation targets. The reviewed literature indicates that no standard, such as OPC UA (open platform communications unified architecture), is used for data transmission or storage in databases. Despite offering flexibility for the data acquisition procedure, the lack of standardised pipelines poses a challenge when repeating experiments since details of the measurement chains, such as technical specifications and processing steps, are usually not reported or not in sufficient detail. Such critical information, however, provides a good insight into the state-of-the-art of modern data acquisition and required preprocessing for ML applications [112].

4.3. Preprocessing and feature extraction

The preprocessing of data, including sensor signals or images, is an important prerequisite for the training procedure of ML models and strongly influences the resulting predictive performance. Preprocessing steps usually include:

- **Filtering and denoising**: reducing the noise level in the gathered data using different filters, such as low-pass filters or Gaussian kernels [120],
- **Replacement of missing values or outliers**: implementing adequate interpolation functions to fill the gaps in the datasets when the instrumentation fails to capture complete data,
- **Normalisation and standardisation**: normalising and standardising datasets with a large variation in the measured ranges as a scaling technique to boost the performance of the corresponding models,
- **Concept drift detection**: detecting a change of statistical properties in the datasets (concept drift) using calibration runs [121] to determine whether a re-training is required to ensure the validity and high performance of the model,
- **Data splitting**: splitting available data into training and testing sets to ensure a proper assessment of the model's performance by independent data [112],
- **Data labelling**: assigning a label to data instances for supervised learning.

A feature representation is a description of data (Section 3.1), for example vectors in $\mathbb{R}^n$, images or graphs. Feature extraction can be used to calculate suitable and informative variables as model input. Statistical features such as minimum, maximum, mean or median value, amplitude range, or standard deviation of a time series are examples of time domain features. Typical frequency domain features are characteristic frequencies and their magnitudes as well as fast Fourier transformation (FFT) features or wavelet features (Table 1). Although many signals can be gathered from a machine tool from which again numerous feature representations can be calculated, various methods such as wrappers, filters, and hybrid methods [122,123] are used to extract the most relevant features to enhance the prediction performance and to avoid deteriorating effects. In this context, unsupervised dimensionality reduction techniques, such as PCA, isometric feature mapping, and locally linear embedding are employed.

5. Review on recent ML modelling in machining

Optimised process parameters can maximise the efficiency of the cutting process during machining, e.g., by increasing the material removal rate [48], minimising tool wear [49], or improving the surface quality [129]. In this manner, thermally induced defects, progressive tool wear, or tool vibrations during the process can be prevented [130]. ML combined with optimisation algorithms can be utilised in advanced machining [130] or manufacturing [131] to autonomously adjust process parameters. As a result, general or specific output quantities, such as process efficiency, quality measures, or production costs, can be optimised. The results of the applied algorithms must be accessible to the process monitoring as well as the control system to enable the adjustment of the corresponding parameters [132].

The reviewed literature revealed that most of the research was focussed on ML applications in machining operations with defined cutting-edge geometries as they offer more opportunities to monitor and observe the cutting operation (Fig. 4a). Milling is the most widely studied process, followed by turning and grinding, while drilling operations have received significantly less attention in this context. This could be due to the complexity of the chip formation conditions, monitoring of process variables, and surface quality characterisation during drilling compared with milling and turning. Fig. 4b demonstrates that among all ML approaches, ANNs are the most frequently applied algorithms in machining-related problems, followed by SVM and RF. Relevant examples of the reviewed literature together with the intended outcomes are presented in more detail in Tables 2, 3, and 4.

Recent applications of ML in machining cover various objectives, typically in one of the fields process characteristics, tool condition monitoring and tool wear, or surface integrity. The following sections provide the state-of-the-art in the respective fields and highlight applied algorithms and the main outcomes.

5.1. Process Characteristics

Process characteristics comprise all properties of a machining process which can be observed during operation or inferred afterwards as a direct consequence of the procedure. These include general characteristics, such as operation time and costs or CO_2 emission, and process-specific characteristics, such as chip formation, cutting forces, or the temperature rise during cutting.

The reviewed literature (Table 2) shows, firstly, that process parameters, such as cutting speed, feed, and depth of cut, are predominantly used as input variables to predict specific process characteristics. This is most probably due to the relatively simple preprocessing procedure and their in-process adjustability [116]. Furthermore, cutting tool properties, including the nose radius of indexable inserts [113], the tool geometry [133], and the coating [94] have also been utilised as input parameters. Secondly, cutting forces were considered most frequently as modelling targets in all studied operations in the literature due to their fundamental effect on the productivity, process performance, and quality of the produced surfaces in machining. Varying cutting forces often cause disturbances of the process. Therefore, a precise prediction of the cutting forces is fundamentally important for process monitoring and control [134]. For example, different ML methods, including ANN, SVR and RA models, were applied to predict cutting forces when milling an aluminium alloy for different cutting parameters [94]. The feed value was found to be the most dominant factor influencing the predicted forces, followed by the tool type and the depth of cut. The authors reported that the ANN approach outperformed both the SVR and RA models in this specific application. An optimisation problem was solved combining the ANN with NSGA-II algorithm to minimise the cutting forces as well as the surface roughness depending on the input parameters.

Different ML modelling approaches, such as ANN [116], GPR [135],

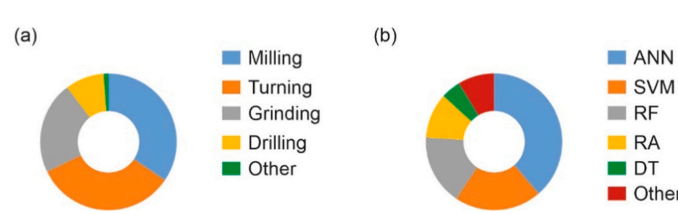

Fig. 4. Reviewed literature of ML in machining: proportions of (a) considered machining processes and (b) applied algorithms.

Table 2
Example applications of ML algorithms and corresponding model input and output for the prediction of process characteristics in machining.

Process	ML algorithm	Model input	Model output	Year / Source
Turning	SVM, GPR	Cutting speed, rake angle	Cutting forces, temperature	2020 / [135]
	ANN, SVM, GPR	Cutting speed, feed, depth of cut, nose radius	Cutting forces	2021 / [113]
	SVM, RF, RA	Cutting speed, depth of cut	Chatter	2022 / [136]
	ANN, SVM	Cutting speed, feed, depth of cut	Cutting forces	2018 / [137]
	ANFIS-ANN	Cutting speed, feed, depth of cut	Temperature	2018 / [116]
Milling	ANN, KNN	Cutting speed, feed, depth of cut, tool diameter	Cutting forces	2019 / [133]
	ANN	Feed, depth of cut	Cutting forces	2019 / [134]
	ANN, SVM, NSGA-II	Cutting speed, feed, depth of cut, coating	Cutting forces	2019 / [94]
	ANN	Cutting forces	Chatter	2021 / [138]
	SVM, RF, KNN, PR	Cutting speed, feed, depth of cut	Cutting forces	2018 / [114]
	ANN	Cutting speed, depth of cut	Chatter	2021 / [68]
	ANN	Cutting speed, feed, depth of cut	Cutting forces	2021 / [139]
Grinding	ANN	Cutting speed, feed, depth per cut, AE	Grinding forces	2020 / [108]
	GPR	Current, voltage	Grinding forces	2021 / [140]
	PSO-SVM	Cutting speed, depth of cut	Grinding forces	2020 / [7]
	GPR, Bayesian	Cutting speed, feed	Temperature	2020 / [141]

and SVM [135], were also implemented for the prediction of temperature rise during machining as technical challenges associated with an accurate temperature measurement constitute the need for reliable predictive models. In this context, the quality and preprocessing of data and the applied ML algorithms significantly affect the accuracy of the predictions as reported in [116]. It was demonstrated that an adaptive neuro-fuzzy inference system (ANFIS) model with a feed-forward backpropagation multi-layer perceptron (BPMLP) with log-sigmoid activation function outperforms the temperature rise prediction compared with an ANN model which was optimised with the Levenberg-Marquardt algorithm.

Table 2 demonstrates that cutting forces are the topic of interest in the majority of ML applications in the field of process characteristics, perhaps due to their influence on process stability and on TMP in almost all of the machining processes. The fact that there are only few studies on temperature and chatter prediction for the considered operations could be linked to the technical difficulties to capture the required high-quality data for the generation of ML models with high performance. This is even more apparent for the prediction of characteristics such as energy consumption as available data is scarce.

5.2. *Tool wear prediction and condition monitoring*

A direct tool measurement is impossible in most of the machining operations. Therefore, indirect tool wear characterisation or predictive models are used to assess the status of the cutting tool. Tool wear prediction (TWP) and tool condition monitoring (TCM) denote very closely, yet different, approaches to estimate the tool life and its performance, respectively.

TWP prediction is the data-based forecast of wear characteristics and the respective tool life via ML algorithms in dependence of the process

Table 3
Example applications of ML algorithms for tool wear prediction and tool condition monitoring with corresponding input parameters and measured variables, respectively.

Process	ML algorithm	Model input		Year/ Source
		Tool wear prediction	Tool condition monitoring	
Turning	ANN, SVM, RF, DT, KNN	-	AE	2021 / [10]
	ANN, SVM	Cutting speed, feed, depth of cut	-	2018 / [137]
	ANFIS-ANN	-	Cutting force	2020 / [142]
	ANN	Cutting speed, feed, material removal	-	2020 / [9]
	ANN	Cutting edge	-	2018 / [149]
	ANN, RF, SVM	Depth of cut, cutting speed, feed	AE, cutting force	2021 / [146]
	ANN	-	Image processing	2019 / [150]
	ANN	-	Spindle current	2020 / [122]
	ANN	-	Cutting force, AE, vibration, acceleration	2020 / [151]
	CNN	-	Cutting forces, acceleration, vibrations	2019 / [152]
	CNN	Cutting speed, feed, depth of cut	Spindle load	2020 / [153]
Milling	1D-CNN	Feed	AE, vibration, spindle current	2021 / [154]
	RF	-	Spindle current, Image processing	2021 / [155]
	RF, SVM	Cutting speed, feed	AE	2019 / [156]
	RNN	Cutting speed, feed, depth of cut	-	2022 / [157]
	RF		Cutting forces	2020 / [158]
	ANN, DT, KNN	Cutting speed	AE	2021 / [159]
	CNN	-	Cutting force	2018 / [160]
	SVM, RF		Cutting forces, current	2019 / [161]
	RF, SVM	Cutting speed, feed, depth of cut		2021 / [122]
	CNN	-	Cutting forces	2018 / [162]
	ANN	-	Cutting forces, vibration	2020 / [163]
Grinding	Fuzzy	Cutting speed, feed, tool diameter	-	2018 / [99]
	RF, MLR (RA)	Dressing speed, dresser width	AE	2018 / [107]
	SVM, kNN-GA	Cutting seed, contact force	AE	2019 / [109]
	RF, MLR (RA)	-	AE, cutting forces, acceleration	2019 / [164]
	RF	-	Image processing	2021 / [147]
	ANN, SVM, RF	-	Image processing	2021 / [148]
Drilling	ANN, SVM, RA	-	Torque	2020 / [14]
	RF	Cutting speed, feed	-	2020 / [165]
	ANN, SVM, SDA	-	Image processing	2020 / [8]

Table 4
Example applications of ML algorithms for product quality prediction with corresponding input and output quantities.

Process	ML algorithm	Input	Output	Year/ Source
Turning	ANN	Cutting speed	Stability behaviour	2019 / [171]
	PSO-SVM, ANN	Cutting speed, feed, depth of cut	Roughness	2018 / [137]
	SVM, RVM, PSO	Cutting speed, feed, depth of cut, vibration, power	Roughness	2018 / [166]
	ANN, SVM, GA-GBRT	Cutting speed, feed, depth of cut	Roughness	2019 / [172]
	ANN	Cutting speed, feed, depth of cut, force, vibration, tool wear	Roughness	2020 / [173]
	ANN	Cutting speed, force	Roughness, Roundness	2021 / [112]
	ANN SVM, CAT (RA), GBR (RA), DT, XGB	Cutting speed, feed, depth of cut, vibration	Roughness	2021 / [174]
	ANN, SVM, GPR	Cutting speed, feed depth of cut, tool	Roughness	2021 / [113]
	RF	Cutting speed, feed, depth of cut	Residual stresses	2019 / [175]
	RF	Cutting speed, feed, depth of cut	Residual stresses	2020 / [176]
	ANN-POA, ANN-PSO	Cutting speed, feed, depth of cut	Residual stresses	2021 / [85]
	ANN-POA, ANN-FPA	Cutting speed, feed, depth of cut	Residual stresses	2021 / [167]
	ANN, SVM, RF	Force, temperature	Microstructural modification	2021 / [13]
	ANN, DT, ElasticNet	Temperature	Thermal damage	2022 / [177]
Milling	ANN	Tool wear, power	Roughness	2018 / [168]
	ANN	Cutting speed, feed, depth per cut, tool	Roughness	2019 / [94]
	ANN	Cutting speed, feed, depth of cut	Roughness	2021 / [178]
	ANN	Cutting speed, feed, depth of cut	Roughness	2020 / [6]
	1D-CNN	Cutting speed, feed, depth of cut	Residual stresses	2018 / [179]
	ANN, RF, DT	Cutting speed, feed, tool wear	Barkhausen noise	2021 / [180]
	ANN, SVR, NSGA-II	Cutting speed, feed, depth of cut	Microhardness	2020 / [169]
	CNN	Tool wear, power	Flatness	2021 / [128]
	DT, SVM	Cutting speed, feed	Flatness	2018 / [181]
	ANN, SMOTE-RF, DT,	Residual stresses, roughness, hardness	Fatigue	2021 / [170]
Grinding	ANN	AE	Roughness	2020 / [108]
	ANN, SVM, GBR	Acceleration, power	Roughness	2020 / [111]
	BR-ANN, SVM, GBR	Cutting speed, feed, workpiece geometry	Roundness	2021 / [182]
	kNN, SVM, RF	AE, power, spindle current	Grinding burn	2021 / [110]
	kNN, SVM RF	Tool, workpiece	Grinding burn	2022 / [183]
	LSTM-ANN, RF	Force, AE, vibration	Roughness	2021 / [86]
Drilling	RF	Force	Concentricity	2020 / [184]
	RF	Spindle current	Roundness	2020 / [185]
	Bayesian Network	Cutting speed, feed, tool coating	Roughness, Roundness	2020 / [186]

design and the parameters chosen. Different combinations of process parameters and variables have been employed for various ML modelling approaches depending on the kinematics of the studied process and cutting tool features as demonstrated in Table 3. The cutting speed, the feed value, and the depth of cut are frequently used input parameters for TWP (Fig. 5), as they can be easily adjusted during a machining process. However, it is reported that the accuracy of the predicted outputs significantly depends on the selected ML algorithm and associated membership functions [142]. Similar to the cutting force prediction (Section 5.1), the ANFIS approach was proven to be a powerful tool in predicting tool wear depending on the cutting speed, feed per tooth, and depth of cut in milling [143]. The PSO algorithm was used to optimise the prediction performance of the model.

While TWP mainly focusses on the prediction of tool life, TCM utilises quantities such as cutting forces, temperature, AEs, or vibrations, which indirectly provide information about the condition of the tool and can be used to assess the wear status via ML predictions [144,145]. In this context, cutting forces [146] and AE signals (Fig. 5) are the predominant input variables in TCM as they can be linked directly to experimentally determined wear mechanisms.

Table 3 shows that AE is the dominant input parameter for TCM in grinding operations, where discontinuous chips are formed and individual cutting edges cannot be defined geometrically [107]. Direct signals from machine tools, such as spindle load [153] and spindle current [154,155], as well as visual characteristics of the produced surfaces, have also been used for TCM [147,148]. In this context, image processing (IP) is proven to be a powerful tool when the produced surfaces are the primary concern and represent the tool performance [148].

In summary, ANN models are widely used for TWP and TCM. In turning operations, CNNs play an important role while other algorithms, such as SVM or RF, are also used for tool performance prediction in milling, drilling, and grinding.

5.3. Product quality

Product quality in machining generally refers to the quality of the produced surfaces for what reason the term surface integrity is frequently used synonymously in this context. The surface can be evaluated by measures of dimensional and geometrical accuracy (e.g., roundness), surface finish (e.g., roughness), or mechanical and microstructural properties of the surface (Fig. 7). As it can be seen in Fig. 6a, the primary cutting parameters cutting speed, feed, and depth of cut were mostly used as input for quality models as they have the most decisive impact on the machining process along with the tool and workpiece material [6]. However, also tool wear and the drive power of the CNC or variables, such as AE and vibrations, can be utilised to automatically predict the surface roughness [168]. Additionally, it was observed that measured process variables, such as AE signals [108,110] and vibrations [86], are predominantly used as input data in ML models for surface quality prediction in grinding. Fig. 6b shows that surface roughness followed by geometrical tolerances are the most widely studied measures to evaluate the surface quality as an output of ML models due to the relative ease of measurements compared with other factors of surface integrity such as residual stresses or microstructural

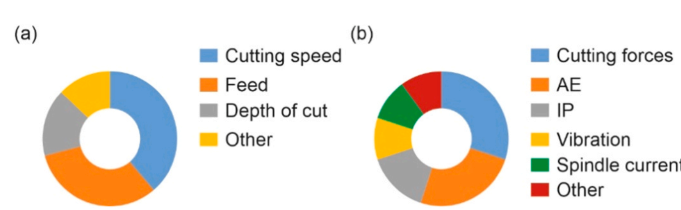

Fig. 5. Reviewed literature of ML in machining: proportions of (a) input parameters for tool wear prediction and (b) input variables for tool condition monitoring (Table 3).

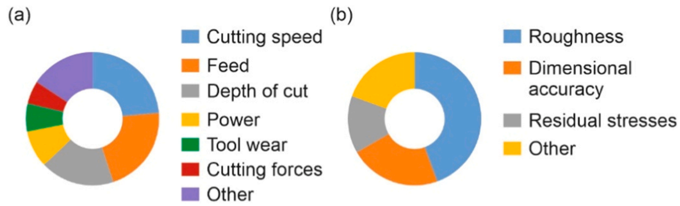

Fig. 6. Reviewed literature of ML in machining: proportions of (a) input and (b) output quantities for product quality prediction in machining (Table 4).

alterations [166].

Comparable with the observed trend for TWP (Section 5.2), ANNs represent the largest group of applied ML algorithms for quality prediction, followed by SVM, RF, and RA, as reported in Table 4. However, a broader range of algorithms, including DT, kNN and Bayesian networks, are used for product quality prediction compared with TWP. In addition to the applied data and algorithms, it was shown that the training procedures have a strong effect on the prediction performance [6]. It was demonstrated that a response surface methodology (RSM) model outperforms ANN models trained by various optimisation algorithms, e.g., quasi-Newton backpropagation, LMA, conjugate gradient or resilient BP. Furthermore, hybrid ANN models optimised by different algorithms, including PSO, the POA, and the FPA were demonstrated to significantly outperform conventional ANNs in the prediction of turning-induced residual stresses [85,167]. In addition to surface roughness and residual stresses, other surface integrity measures, including microstructural alterations [13] and subsurface microhardness [169], have also been predicted using ANNs and SVMs, respectively. In turn, these could be used as inputs for a further ML modelling of fatigue effects at machined parts, e.g., via DTs and partial least squares regression analysis [170].

6. AI-based total performance optimisation

In the present section the findings of the reviewed literature in machining will be summarised and the importance of MOO for successful TMP will be worked out and discussed.

6.1. From ML prediction to process optimisation

The simultaneous consideration of all parameters and variables affecting TMP is required to achieve the overall optimisation of machining processes. This directly implies the need for modelling various process-related targets and integrating different MOO methods for their simultaneous achievement. Targets corresponding to product quality, tool wear, and process characteristics (Sections 5.1 to 5.3) have been extensively investigated in recent years. Most of the ML applications in machining can be described as the following approaches:

i. using an ML algorithm to model the relation between process input and output and subsequently selecting appropriate inputs for an optimal output by an appropriate optimisation algorithm [4,187],
ii. directly calculating the optimisation objective (e.g., using a fitness function for GAs) without a need for a preceding ML modelling to apply the optimisation algorithm [45],
iii. using an ML model to predict the outcome of a process from input parameters without direct exploitation of the result in an optimisation algorithm. In this case, the optimisation occurs indirectly in form of online monitoring [154] or process comprehension from the ML predictions [8],
iv. applying optimisation techniques for the hyperparameter tuning process to find an optimally parameterised prediction model [7,8,85,174],
v. investigating optimisation techniques for the training of ML models, e.g., ANNs [94,116,151].

According to the literature research, the data-based adjustment of machining parameters in the sense of (ii.) is mostly realised via data-based heuristic optimisation techniques such as GAs. Few authors describe optimisation approaches as mentioned in (i.) based on the prediction of an upstream ML model [21]. Many AI applications in the field of machining were found to successfully generate an ML model for the automatic, data-based prediction of relevant process quantities according to point (iii.) above, without a subsequent optimisation step. However, it is important to note, that the last two approaches, i.e., (iv.) and (v.), have only an indirect influence on the process optimisation by finding the most appropriate predictor function for a given learning task. Fig. 7 demonstrates the correlation between various process parameters and variables with the potential targets in ML modelling to define objective functions to address the required criteria for TMP. The aim of SOO and MOO in the context of TMP optimisation is finally to calculate optimal values for process parameters, such that their feedback in the actual process results in improved machining results. The solid lines in Fig. 7 describe that there is a direct link between the demonstrated entities. For example, process parameters directly affect the ML targets of process characteristics, tool wear and TCM, as well as the product quality, while the broken lines denote an indirect impact. Generally, the TMP can be optimised according to the three interdependent criteria of product quality, processing time, and processing costs. These criteria are strongly correlated with the factors surface finish, dimensional accuracy, tool-wear rate, and chip breakability [11].

Product quality can cover one or more aspects of surface integrity, geometric and dimensional accuracy, residual stresses, microhardness, and other properties of the machined products (Section 5.1). The processing time can best be assessed via the material removal rate (MRR) and, hence, the production rate in machining. Although alteration of cutting parameters could lead to higher MRR values, this may negatively affect the surface integrity, i.e., increased roughness or residual stresses, the tool life through an increased wear rate, and process sustainability due to an increased energy consumption and demands for more coolants. The production costs also depend on the MRR, costs associated with the raw material, and process consumables, including cutting tools. Depending on the machining process at hand, the three criteria time, costs, and quality affect the TMP to varying degrees which should be captured by ML and optimisation models based on a meaningful database.

6.2. Single-objective and multi-objective optimisation in machining

As explained previously, the aim of SOO is to optimise one objective function with respect to the inputs. The inclusion of the optimal process parameters via a feedback control system back to the process leads to the actual desired improvement of the machining process. The cutting conditions, i.e., cutting speed, depth of cut and feed rate, and to some extent cutting tool materials and characteristics, are the most important and flexible parameters for process optimisation in machining. Observable and measurable variables such as AE or acceleration signals can be used to predict target quantities, but due to their uncontrollable nature they cannot be used for optimisation in the strict sense. If they are used as model outputs, they can be optimised themselves depending on process parameters. As further objectives and potentially contradictory effects of different targets are ignored, SOO limits the optimisation result to a single aspect [47]. MOO, in contrast, considers multiple target quantities and, therefore, leads to a simultaneously optimised set of objectives and corresponding inputs [188]. It can yield SOO as a marginal case for the TMP optimisation [43].

The modelling of multiple targets in the form of ML predictions can be regarded as a preliminary step or precondition for an MOO. Different ANN models are, for example, utilised to predict different aspects of

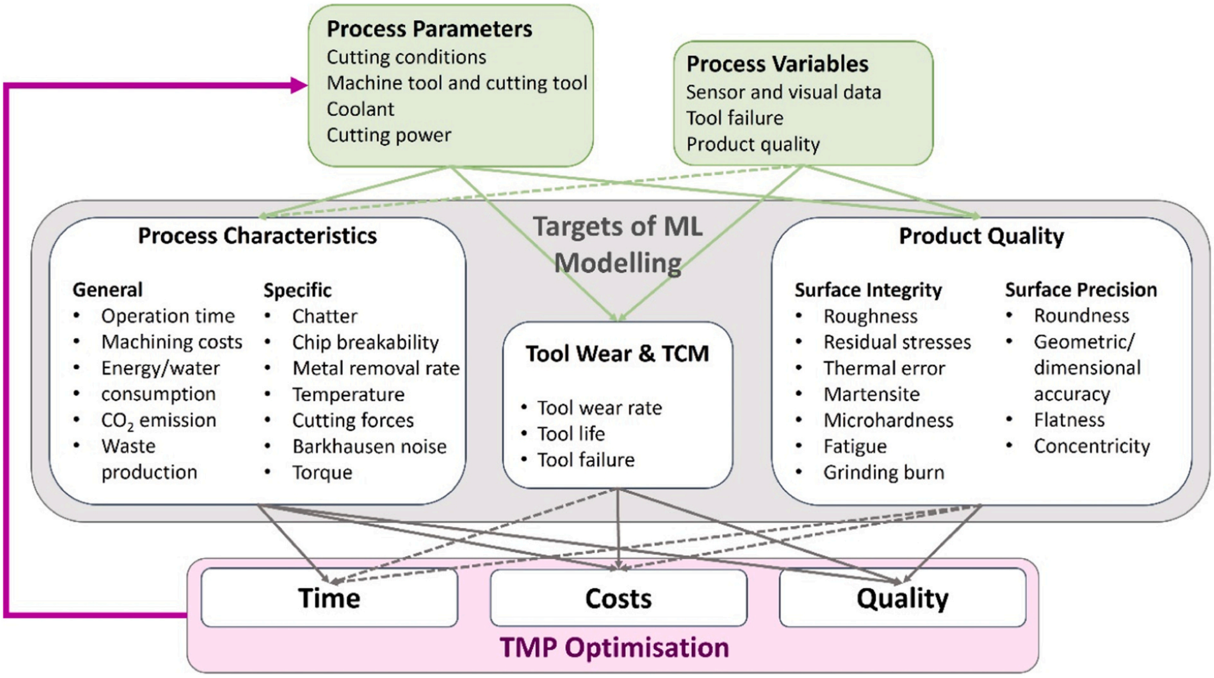

Fig. 7. Overview of TMP optimisation: process parameters and variables as ML model inputs, outputs of ML models as optimisation targets, and the main TMP optimisation criteria time, costs, and quality.

surface quality [112] or tool wear and roughness [154] from measured vibrations, forces, sounds, or spindle current signals. Similarly, residual stresses [85] or surface finish and dimensional deviation [36] are predicted from the cutting conditions using ANNs. Classical ML algorithms such as kNN, SVMs, DT, and RF [122,135,140] or fuzzy set models [11] are also implemented in multiple regression and classification tasks which assess machining processes.

As for SOO, MOO can be performed based on different ML approaches and modelling (cases (i.) and (ii.) in Section 6.1). In the first case (i.), ML algorithms, such as ANNs, RF, and SVMs, are used for the prediction of forces, tool edge chipping, and surface quality with and an additional optimisation algorithm is utilised to determine the optimal cutting conditions [94,100,158]. A prediction from analytical, empirical, and numerical model components as fitness function for GA [12] represents a hybrid approach of (i.) and (ii.). However, MOO is frequently performed without a preceding ML modelling. Instead, a data-based optimisation algorithm is calculated directly with respect to a measurable or computable objective function. In this context, evolutionary algorithms, such as NSGA-II [43,50,189,190] or PSO [46,190], as well as the RSM [47,48] and grey relational analysis [48,188] play an important role.

The presence of conflicting objectives is a general disadvantage of MOO which results in so-called Pareto-optimal solutions [43,189,191]. These are overall best solutions that are potentially suboptimal with respect to single optimisation criterion. It is, however, mathematically feasible to deal with multiple objectives via the introduction of constraints [44,45] or an SOO approach of a sum or other functional relationship of individual optimisation targets [41].

Generally, ANNs in their different forms followed by SVMs are the most frequently used ML algorithm in various applications related to machining operations. This can be explained by the fact that neural networks are able to generate the necessary feature representation of data for the learning task at hand as a part of the learning process. Additionally, they can handle multiple, dependent input parameters, as it is typical for manufacturing processes like machining. This capacity of ANNs is at the expense of a low explainability, which inhibits the deployment of neural networks in industrial applications. In contrast, SVMs require an appropriate feature representation of data from a preprocessing procedure, but they are explainable or interpretable by design. With respect to the algorithms for process optimisation in machining, the heuristic approaches of evolutionary algorithms, such as GAs, played the dominant role in recent years. The predominance of data-based heuristic methods can be explained with the fact that the objective functions frequently cannot be calculated as closed formula. As no information of function values or derivatives are available, heuristic approaches can be employed successfully in compensation. In the future, known properties of the objective function or its derivatives could increasingly be included to the process optimisation approach.

6.3. Challenges and success factors

The solution of MOO problems as a mathematical task meets computational challenges such as, e.g., the search for global optima or the compromise between Pareto-optimal solutions and optimal values for single-target objectives. Also the convergence rate [50], overfitting, and large datasets for the training of DL algorithms [28] pose problems for the practical implementation. Other limitations of online-monitoring and process improvement are real-time predictions [10,192] and the actual implementation of optimisation results at the production plant [4].

To achieve the demanding aim of TMP [11,12] optimisation, the following key success factors were identified:

- ML prognoses by itself are beneficial for process monitoring or related applications. A true improvement of a machining process with respect to resources, costs, and product quality can only be achieved if optimal process settings are determined by an optimisation procedure and if these settings are used in the actual process.
- Three classes of objectives along the process chain (refer to Section 3) have been identified, to which the precise quantities from SOO and MOO can be assigned (Fig. 7). In order to ensure a holistic view on the machining process, the TMP must necessarily be evaluated by means of a consideration of all three classes via MOO [11,41,44,46].

- The inclusion of the ML and optimisation results into the process is crucial in practise, either for an immediate regulation or for a future process design and planning. Therefore, a pipeline on the basis of software and hardware must be installed which particularly comprises the database, continuous integration and continuous deployment (CI/CD) tools for the industrial implementation [4,26], and a visualisation platform for in-process or online monitoring [126,154].
- Production plants are typically equipped with multiple sensors which permanently deliver sources of information about the process (either from the beginning or as a result of retrofitting). As the TMP optimisation exactly requires this variety of information, an effective sensor fusion procedure for the ML modelling should be integrated [36,118,127,154,192].

Apart from these key factors which are deemed to be necessary for the TMP optimisation, there are further modelling aspects that are not extensively researched, but significantly contribute to the machining process improvement. These include a broader observation of cause-effect relation chains that support the idea of TMP without limiting a complex problem to a single cause-effect relationship [193]. Additionally, further investigation about the quality and quantity of the used data [20], as well as the selection of the best model for given learning tasks in the context of machining [28] increases the performance of predictive models. Finally, as soon as a prediction and optimisation can be used successfully for the in-process regulation, the question about the reusability of models emerges. Transfer learning can be used to adapt ML models for the variation of conditions or other related processes that will be the basis for a sustainable, flexible, and robust application of AI in the near future [183,194]. ML models should be continuously retrained or adapted using various continual and transfer learning approaches [178] to avoid the drift in their prediction [181] and performance loss over time due to changes in the input data, the tool, or the environment. To sum it up, this review paper identifies the issues energy and CO_2 reduction [48,50,188], sustainable machining in general [18], transfer learning techniques [157], and effective MOO [93] as the most relevant future topics in AI-based research on process optimisation in machining.

7. Conclusion

In recent years, considerable research activity has been conducted to reliably model parameters and variables in machining. Machine learning (ML) and, in a broader context, artificial intelligence (AI) used in conjunction with data-based optimisation have become standard tools for analysis and monitoring of machining operations. They offer great potentials for a holistic view and improved design of cutting processes. Process characteristics and loads, resulting tool wear, and produced surfaces properties can be predicted via ML depending on cutting conditions, the used machine tool, and other process data for a variety of machining operations including milling, turning, drilling, and grinding. Quantities, such as cutting forces or tool wear are reported to be used both as input and output for ML models, which is the prerequisite for prediction and optimisation along the whole process chain with AI. The predominant scenarios in the studied ML applications were found to be supervised regression and classification, which refers to learning a predictor function for a real-valued or discrete process information using labelled data. In general, the growing importance of DL due to improved storage and calculation capacities and the emergence of large data volumes with high frequency and dimension is reflected by the increasing deployment of ANNs within ML applications in machining. However, the majority of the reviewed literature reports on a successful generation of a single prediction model and its evaluation without an explicit optimisation step regarding a process-related objective function. ML predictions are very useful for condition monitoring and predictive maintenance. The actual ML models can serve as objective functions, however, they do not directly lead to a process improvement. To this aim, mainly data-based evolutionary optimisation algorithms such as GAs for SOO or NSGA-II for MOO are applied to determine process parameters for an optimal machining quality.

MOO has been constituted as precondition for TMP optimisation on the way to advanced machining processes. Future research is required to consider targets related to fair and sustainable machining, in particular, to energy and CO_2 reduction in TMP. In this context, continual and transfer learning techniques will likewise support the efficient consumption of resources and provide a persistent adaption of the AI component.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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