KSME

Springer

Journal of Mechanical Science and Technology 36 (1) 2022

Invited Review Article
DOI 10.1007/s12206-021-1201-0

Artificial intelligence enabled smart machining and machine tools

Yu Sung Chuo[1], Ji Woong Lee[2], Chang Hyeon Mun[3], In Woong Noh[2], Sina Rezvani[1], Dong Chan Kim[3], Jihyun Lee[1], Sang Won Lee[2] and Simon S. Park[1]

[1]Department of Mechanical and Manufacturing Engineering, University of Calgary, 2500 University Dr. NW, Calgary, Alberta, Canada, [2]Department of Mechanical Engineering, Graduate School, Sungkyunkwan University, 2066 Seobu-ro, Jangan-gu, Suwon-si, Gyeonggi-do, Korea, [3]Department of Mechanical Engineering, Ulsan National Institute of Science and Technology, 50 UNIST-gil, Ulsan 44919, Korea

Keywords:
· Artificial intelligence
· Industry 4.0
· Machine learning
· Machine tools
· Machining

Correspondence to:
Simon S. Park
simon.park@ucalgary.ca

Citation:
Chuo, Y. S., Lee, J. W., Mun, C. H., Noh, I. W., Rezvani, S., Kim, D. C., Lee, J., Lee, S. W., Park, S. S. (2022). Artificial intelligence enabled smart machining and machine tools. Journal of Mechanical Science and Technology 36 (1) (2022) 1~23. http://doi.org/10.1007/s12206-021-1201-0

Received March 30th, 2021
Revised August 30th, 2021
Accepted October 8th, 2021

† Recommended by Editor Hyung Wook Park

Abstract Artificial intelligence (AI) in machine tools offers diverse advantages, including learning and optimizing machining processes, compensating errors, saving energy, and preventing failures. Various AI techniques have been proposed and applied; however, many challenges still exist that inhibit the use of AI for machining tasks. This paper deals with different types and usage of AI technologies in machining operations such as predictive modelling, parameter optimization and control, chatter stability, tool wear, and energy conservation. We discuss the challenges of AI technologies, such as data quality, transferability, explainability, and suggest future directions to overcome them.

1. Introduction

In the manufacturing industry, there is growing interest in the implementation of machines that are capable of learning and adapting to their environment to optimize manufacturing processes. This new wave of technology has been given many names, including “Industry 4.0”, “digital manufacturing”, “cyber physical systems”, “internet of things (IoT)” and “smart factories”. Regardless of names, embedding sensors into manufacturing tools and analyzing the resulting data with AI can address many shortcomings in modern manufacturing processes; machines that can learn from their work can improve efficiency and reduce production costs by optimizing workflow, enabling predictive maintenance before a failure, and increasing precision of machining processes. This will result in productive and adaptable production lines capable of meeting the ever-changing needs of consumers.

A report by PricewaterhouseCoopers indicated that 91 % of industrial companies are investing in digital manufacturing [1]. Furthermore, it was reported that over US$900 billion was invested in such initiatives in 2016 [2]. One particular area of interest for the application of AI is machining or subtractive manufacturing. Subtractive manufacturing accounts for an estimated 5 % of the developed worlds’ GDP, with a market size that is expected to reach US$43.73 billion by 2026 [3]. There is also strong economic motivation for the monitoring of tool condition and process parameters using sensors and AI. It was projected that the manufacturing sector in the United States alone would spend US$6.99 billion on machine tools in 2020 [4]. Extending the tool life by optimizing the machining process and accurately predicting when to replace new tools would reduce expenses related to replacing the tools. The implementation of AI could also cut costs associated with minimizing failures and machining errors. A majority of manufacturing defects result from human errors. Thus, enabling machines to learn and adapt to optimize machining processes could result in significant economic benefits.

The development of this new technology, however, presents its own challenges. AI models require large amounts of accurate data to operate successfully. If the dataset given to a model is too small or contains inaccuracies, then the model will provide inaccurate results. It is also difficult to transfer AI models between different machines. Additionally, the reasoning of AI models is not easily understood since they do not use traditional, physics-based approaches to

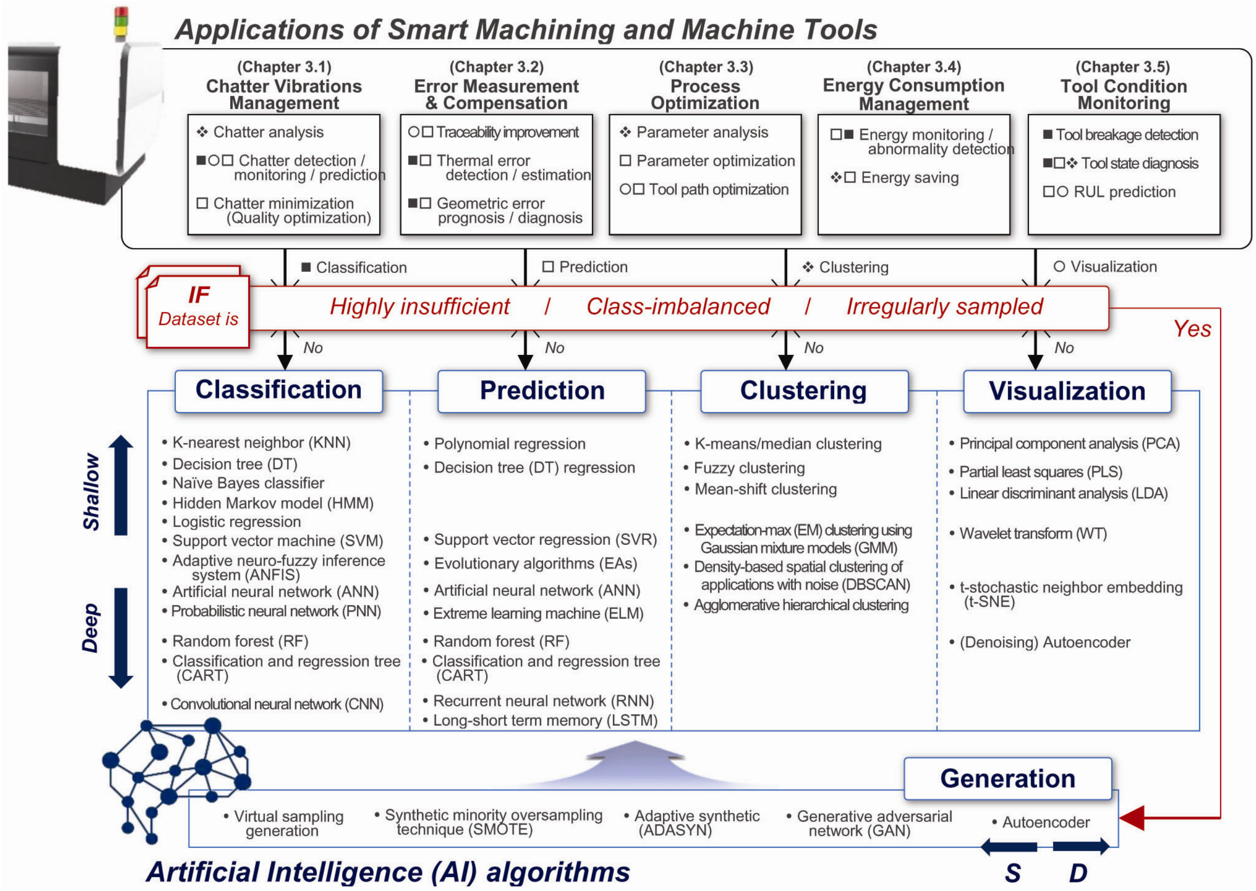


Fig. 1. Schematic diagram of applications of AI algorithms for smart machining.

solve problems. Therefore, AI models must be equipped with sufficient reasoning algorithms to mitigate false alarms when performing diagnostics.

This paper provides an overview of the use of AI in machining processes. The motivations behind the use of AI are discussed for solving different problems, along with current applications of AI in machining research. In the context of subtractive manufacturing, researchers have been applying various AI models to achieve machine automation, sometimes comparing different models for fulfillment of certain objectives. Some examples include chatter in machining operation, tool wear and breakage mitigation, parameter optimization, error compensation, and energy conservation. Several researchers have been investigating new techniques such as automatic data collection and data analytics, to address these traditional machining challenges. The future of AI implementation is outlined including challenges facing current models, suggested improvements and opportunities.

2. Different types of artificial intelligence approaches

In order to apply AI to machining systems in the right place, it is necessary to identify the types of AI. AI is subdivided by 'cognitive level' and 'modeling implementation stage'. Fig. 1 shows a schematic diagram of how the types of AI algorithms are applied to the applications of smart machining covered in this paper. The algorithms are arranged according to the depth of each model architecture. A deeply designed algorithm can take into account more variables and produce high accuracy trained results, but it requires more data and can easily lead to overfitting error. Shallow algorithms are relatively inferior to deep algorithms in terms of the training performance but can work well with small amounts of data and generally provide a more interpretable reasoning process.

AI's cognitive level, the first aspect of AI categorization, can be related in terms of similarity to human's cognitive level, and it is classified into four levels: Reactive, limited memory, theory of mind, and self-aware [5, 6]. Table 1 illustrates the cognitive levels.

The second criterion for AI categorization is how the model is built, and from this perspective, AI models are divided into rule-based and learning-based. The rule-based models are established by the logical reasoning process, generally IF-THEN rules, based on the corresponding domain knowledge, as expert systems. Fuzzy theory is a representative logic for the rule-based model that infers a proper result by using membership functions and defuzzification rules defined by experts. The

Table 1. Types of AI's cognitive level.

Reactive machine	Limited memory	Theory of mind	Self-aware
- Responds to external stimuli by programmed logic - Shows understandable rationales for the result - Suitable for simple tasks - Developer must be an expert for the tasks - Most of AIs before machine learning falls into this level	- Makes new decisions through memories of previous experiences - Analyzes the new data by pattern recognition - Able to handle complex and difficult problems - All existing AI models come under this level	- Understands fundamental meaning of tasks - Interacts with human intentions and emotions - Explores comprehensive and fundamental optimum - No practical cases yet	- Self-development based on human-like or higher cognitive abilities - No longer relies on human education

rule-based AI models mostly fall into the ‘reactive machine’ phase introduced in Table 1 and thus have the advantages of transparent decision-making and easy modification. However, when the number of variables involved in the result is vast, it is difficult to define clear logic, and the performance of the model becomes poor. If the target information to be inferred by AI has a defined causal relationship and requires a clear reasoning process, a rule-based model is worth considering.

The learning-based approach, also known as machine learning, is a modeling methodology that belongs to the 'limited memory' stage in terms of cognitive level. The machine learning can be said to apply to majority of AI systems in use today. Depending on the learning principle, machine learning models are classified into supervised, unsupervised, and reinforcement learning methods [7].

Supervised learning is a methodology that trains AI using a data set in which the correct answer is matched to each data sample and makes the model to output an appropriate result for a new data. It is advantageous for efficient and accurate learning by self-exploration of the correlations between data and output information. However, it is not easy to prepare a well-organized training data set for supervised learning, and it requires tremendous data-processing work if the amount of data is very large.

Meanwhile, an unsupervised model is trained to identify the characteristics of a data set using only data without designated answers and to assign the specific features for new data. This type does not require the labor-intensive work in the data preparation step unlike supervised learning, but it is sometimes difficult to understand the exact meaning of results. Therefore, in recent years, some AI modeling methods in which supervised and unsupervised learning are integrated to compensate each other's shortcomings have been proposed.

During reinforcement learning, an AI agent performs repetitive actions in a given environment based on a behavior strategy called policy and trains the model to be optimized through rewards for actions. Well-trained AI agents often provide innovative solutions that humans have not thought of, but setting up an independent and complete environment for reinforcement learning is very difficult, and the training process can take days to even weeks. In the recent smart manufacturing field, a concept of creating a reinforcement learning environment using the digital twin system has been proposed [8, 9].

On the other hand, a number of notable AI models that support industrial decision-making have been recently studied based on a deep learning approach. The deep learning refers to an AI modeling method using neural networks with many hidden layers, and it has emerged as a major machine learning field since the publication of Hinton’s paper in 2006 [10], which confirmed that even deep-layered neural networks can be efficiently trained if the initial values are well defined. The deep learning algorithms are characterized by including self-feature extraction layers customized to specific data types to effectively learn high-dimensional data; convolutional neural network (CNN) specialized for image recognition and recurrent neural network (RNN) tailored for natural language processing are representative. Therefore, in case of training big data to solve complex problems lacking domain knowledge, the deep learning algorithms often show strong performance. However, the deep learning requires a sufficient amount of training data to avoid overfitting, and a trained model tends to be difficult to interpret, so the algorithms should be carefully selected as AI modeling methods.

As a third perspective, a pragmatic AI categorization scheme focusing on the perspective of applying algorithms to machining is introduced. This has been defined by reorganizing the purpose and characteristics of the AI algorithms based on several review papers that summarized a large number of algorithms applied to machine tools and smart machining [11-13]. Consequently, AI algorithms could be divided into five types of purposes: classification, prediction, clustering, visualization, and generation, according to the form of output information, which is an essential factor in selecting suitable algorithms.

Table 2 illustrates a number of representative algorithms for each category, and their characteristics.

Classification is the main purpose of applying AI algorithms. These algorithms output the corresponding class for the input data, and they are mainly applied to detect and diagnose faults or abnormal conditions. The softmax-based multilayer perceptron (MLP), which has the same representation as standard artificial neural networks (ANN), is the most popular learning-based classification algorithm. Support vector machine (SVM), k-nearest neighbor (KNN), and naïve Bayes classifier are also frequently used in the case of classifying five or fewer classes. Convolutional neural network (CNN) series and ensemble series including random forest (RF) are widely applied to classify

Table 2. Types of AI algorithms and their characteristics from the application point of view.

Categories	Algorithms	Characteristics
Classification	• Artificial neural network (ANN) • Support vector machine (SVM) • Decision tree (DT) • K-nearest neighbor (KNN)	- Most frequently used classification algorithms - Generally suitable for larger datasets in the following order: ANN > SVM > DT > KNN
	• Naïve Bayes classifier • Logistic regression • Hidden Markov model (HMM)	- Probability-based classification algorithms - Effective modeling with relatively small datasets
	• Adaptive neuro-fuzzy inference system (ANFIS)	- Hybrid version of fuzzy inference system and ANN to reduce the need for domain knowledge - Effective for classifying relative levels
	• Convolutional neural network (CNN) • Random forest (RF)	- Popular deep learning and ensemble algorithms - Suitable for large datasets
Prediction	• Artificial neural network (ANN) • Polynomial regressions	- Most frequently used prediction algorithms - ANN requires larger datasets than regressions do
	• Support vector regression (SVR) • Decision tree regression (DTR)	- SVM and DT combined with regression principle to transform the classifier into predictive models
	• Evolutionary algorithms (EAs)	- Effective in tracing the optimal value within a set boundary condition
	• Extreme learning machine (ELM)	- Derived version of ANN with improved learning efficiency of gradient-based back-propagation
	• Recurrent neural network (RNN) • Long-short term memory (LSTM)	- Suitable for prediction of values with sequential meaning (e.g. prediction of remaining useful life)
Clustering	• K-means clustering	- Representative clustering method based on statistics - Need to pre-define the number of clusters [14]
	• Mean-shift clustering • Density-based spatial clustering of applications with noise (DBSCAN)	- Valid when the number of clusters cannot be pre-defined or when shifting specific statistics in uneven data distribution [14]
Visualization	• t-Stochastic neighbor embedding (t-SNE) • Principle component analysis (PCA)	- Unsupervised dimensionality reduction method - t-SNE is usually more effective at visualizing the distance between each data sample [15]
	• Partial least squares (PLS) • Linear discriminant analysis (LDA)	- Supervised dimensionality reduction method - Require labeling of data samples
Generation	• Generative adversarial network (GAN) • Autoencoder (AE)	- Applied when virtual data similar to actual one is required (e.g. class imbalance problem) - Require large datasets

more than five classes or to extract further detailed information. Rule-based algorithms such as decision tree (DT) and fuzzy inference system (FIS) can also deal with classification problems, but their performance is insufficient to handle recent complex systems. Therefore, hybrid-type algorithms such as adapted neuro-fuzzy inference system (ANFIS) have been proposed. These classification algorithms have the powerful advantage of being able to easily utilize the models because they provide a deterministic answer selected from trained labels. On the other hand, there is a limitation - a result of a classifier is only within the predesignated labels even if an outlier that greatly deviates from the distribution of trained data set is entered into the model. To overcome this limitation, classification models are occasionally designed in conjunction with clustering or visualization models to periodically update the label set or provide information about the data samples outside of the typical data distribution.

Predictive algorithms output real values, so they can be applied to objectives such as status monitoring, process optimization, remaining useful life (RUL) prognosis, etc. Artificial neural network (ANN) as multilayer perceptron (MLP) is the most widely used algorithm in predictive models so far and is often a standard for comparison with other proposed modeling techniques. Polynomial regressions, and evolutionary algorithms (EA) as genetic algorithms (GA) are found in many applications for relatively simple tasks. Since the predictive models are constructed by uncategorized real values, it is very sensitive to outliers in the modeling process, so sophisticated data preprocessing such as normalization is required. In particular, processing high-dimensional data needs expertise in data science. Nevertheless, predictive models can take major roles in AI-based smart systems because they are very versatile.

Clustering algorithms output the result of classifying data samples with similar properties into the same group in an unsupervised manner. This type is mainly applied to identify outliers or obtain some beneficial insight from collected data. Dimensionality reduction techniques are sometimes used together to compensate for the weak point of clustering models, which is poor performance in high-dimensional data. Since the clustering models provide only qualitative results in terms of data analysis, it is difficult to apply them to automated systems alone, but they can be applied as a preprocessing step to improve the performance of classification and prediction models.

The fourth type, visualization algorithm, is applied to monitor the change of data trends or to analyze the trend in conjunction with a clustering algorithm. Visualization models output the result of reducing high-dimensional data to three or less dimensional data that humans can visually perceive and are divided into models that learn in supervised and unsupervised manners.

Generative algorithms have recently attracted great attention in the field of industrial AI application, where it is difficult to obtain a satisfying data set. While the previous four types of algorithms output information, whether it is quantitative or qualitative, the output of a generative model is data that is similar to real data but does not actually exist. There are three main reasons why data generation is necessary for the industrial fields including machining: insufficient supply of data, class-imbalanced data sets, and irregular data collection. To cope with low data quality, approaches at the data level such as data imputation have been conventionally used, but many approaches at the algorithm level focusing on generative models also have been proposed recently. The generative adversarial network (GAN), which has raised the generative type to one of the main algorithmic categories, is trained to create virtual data close to actual data samples in the distribution of high-dimensional data, and the performance of data imitation is gradually updated to be indistinguishable from real data by a discriminator. Autoencoder (AE) is also a popular generative algorithm that produces a representation similar to input data through a reduced encoding network using an unsupervised method. These generative algorithms can perform important roles in solving fundamental problems of AI models that highly depend on the data quality. Meanwhile, like how a photograph of virtual people is seen and judged to be similar to real people's appearance by human beings, the generated virtual data should be determined to be similar to actual data by humans or more accurate criteria, especially before utilizing it to train other AI models. However, for the raw data from industrial sensors, such as vibration and noise, that kind of reliable judgement is nearly impossible, and there is no way other than relying on the stochastic similarities used in the modeling process. Therefore, to improve the reliability and utilization of generative algorithms in industrial sites, further studies related to data quality issues will be consistently needed in the future.

Different types of AI were introduced according to three kinds of perspectives. From the first perspective, AI was divided into four stages depending on the level of thinking ability to be able to recognize things, and nearly all existing AI models have remained in the second level. The second point of view was the difference in the principles under which AI models were constructed, and the learning-based approaches have been most widely used in recent years due to applications that require consideration of complex variables. The classification criterion from the third perspective was the form of information that the algorithm outputs, and representative algorithms for each type and some hybrid manners that complement each other's types were briefly introduced. Understanding these classification schemes is expected to support customized AI applications for various objectives of smart machining and machine tools.

3. AI in machining

In order to improve the quality and productivity of machining operations, both preventive maintenance and corrective actions must be undertaken. Often, chatter vibrations limit the overall machining productivity rather than the machine tool torque or speeds. Moreover, errors, tool wear and breakage, tool path or process optimization, and energy conservation need to be addressed. Traditionally, physical model-based approaches have been used to overcome these problems; however, there have been limitations in solving the challenges due to non-linearities, varying parameters, and uncertainties. Advances in AI methods in machining and machine tools offer the potential to overcome these challenges by collecting and analyzing appropriate data. This section investigates the implementation of AI and other smart functions from the perspectives of traditional machining challenges, improvement opportunities, and controllable parameters.

3.1 Chatter vibrations management

Variation of chip thickness during cutting operations results in a self-excited vibration called regenerative chatter vibration. This phenomenon can decrease the efficiency of machining processes and results in poor quality of finished products. Therefore, chatter stability analysis is required prior to starting any machining operation in order to assess whether the process generates chatter or not. There are many factors affecting chatter stability including machine-tool dynamics, cutting tool geometry, cutting conditions, and workpiece material. Chatter could be nonlinear at low cutting speeds, which requires the inclusion of process damping in the models. Fig. 2 shows a two-degree-of-freedom (2DOF) milling operation model. This physics-based analytical model is used to analyze chatter with a frequency response function of structural dynamics and mechanistic coefficients of the force model, along with the number of teeth, diameter, and radial depth of cut. Stability analysis using a physics-based analytical model, however, has limitations in accurately predicting due to non-linearity, changing dynamics from rotational speeds, and changes of cutting constants due to the magnitude of instantaneous chip thickness and orientation of the vibrating tool or workpiece [16].

Few AI techniques have been proposed for chatter stability analysis and prediction. Cherukuri et al. [16] developed an artificial neural network (ANN) to model stability in turning. A data set that trained the ANN was generated from an analytical

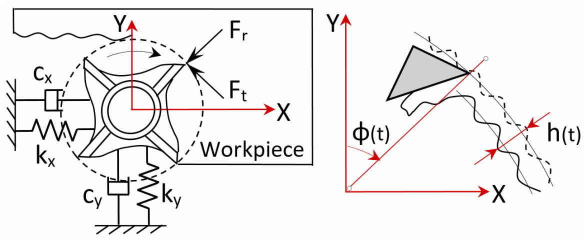
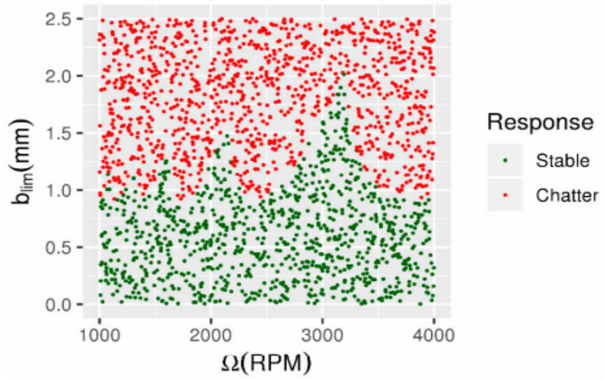
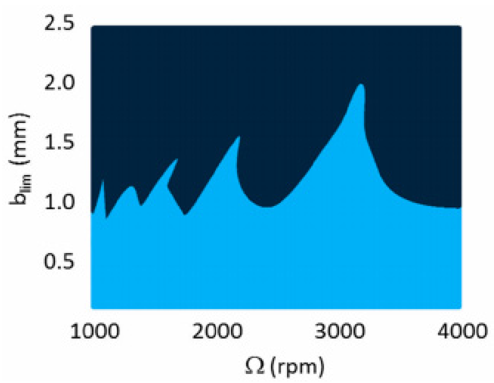


Fig. 2. 2DOF milling operation (left) and chip thickness variation during operation (right).



(a)



(b)

Fig. 3. Chatter stability using ANN: (a) ANN training; (b) predicted decision boundary [17].

physics-based stability limit. In the case of chatter prediction, the problem is of binary classification, since the output predicts whether a given set of inputs leads to chatter or not. A model was defined in the test domain of spindle speed and chip thickness in which experimental stability results are collected and the ANN model uses those to update in training. The gradient descent method is a way for updating the weights at each neuron, which includes the derivative of error with respect to the weight. A learning rate can be used to control the magnitude of correction. Due to the complexity of the gradient calculation that can arise from an ANN with multiple hidden layers, the approach used the resilient backpropagation algorithm that has a different learning rate for each weight, and during the training process, the rates can be adjusted to accelerate convergence. Furthermore, only the signs of derivatives were used in place of derivatives. The ANN considered had two hidden layers with six neurons in each layer. An analytical turning stability limit was used to generate training data from the frequency response function (FRF), mechanistic cutting coefficients, and the geometry. The training data set generated from the analytical model consisted of 2001 points, using the stability boundary depicted in the Fig. 3(a). After training, using spindle speed and limiting chip width as inputs, the predicted stability boundary is shown in Fig. 3(b) in comparison with the actual boundary. The result is not accurate near lobe peaks and some troughs. The overall accuracy of the model is 99.4 % using a test data set of 501 points [17].

Karandikar et al. [18] used Bayesian machine learning to predict chatter stability in milling, using the criteria of spindle speed and axial depth of cut. Experiments were used for training, which updated the probabilities using Bayes' rule. Fu et al. [19] used deep belief network trained with vibration signal from end milling to predict chatter stability. The training was done with greedy layer-wise strategy, where optimal choice was made one layer at a time, and fine tuning of the model was done with back propagation. The concept of using AI approaches in chatter prediction has been proven for standalone conditions by considering the process parameters. Opportunities exist to extend the AI predictions for more variables, such as process damping. This will improve the applicability to a wider range of scenarios.

Neural networks using input data from signal analysis on piezoelectric accelerometers were used to develop data-driven AI models to detect slot milling stability. Signals from the sensors were processed using multiband filtering resonance, then went through the envelope treatment to increase signal to noise ratio and sensitivity. The resulting features were separately classified by neural networks built on a radial basis function and multilayer perceptron [20]. A vector based on the standard deviation of wavelet transforms and the frequency band's wavelet packet energy ratio was developed for chatter detection in conjunction with a piezoelectric accelerometer in a boring process. For pattern recognition, a support vector machine (SVM) with a radial basis function kernel was generated from the vector, which classified three categories: stable, transition, and chatter. A state recognition accuracy of 95 % was achieved after training with experimental data [21]. This technique can be used with, for example, cutting forces and spindle vibration in frequency and discrete time domain. Continuous wavelet transform (CWT) was used on signals from a dynamometer in end milling to convert them to two-dimensional scalogram images, that represent frequency variation with time. A convolutional neural network (CNN) was served with the scalogram inputs to identify stable, transition, and chatter states, with accuracy of 99.1 % [22]. Data from piezoelectric vibration and force sensors, and acoustic emission sensors for machining conditions, and laser displacement sensor for surface, were used to train a support vector regression model to relate the phenomena in grinding operation. The result was

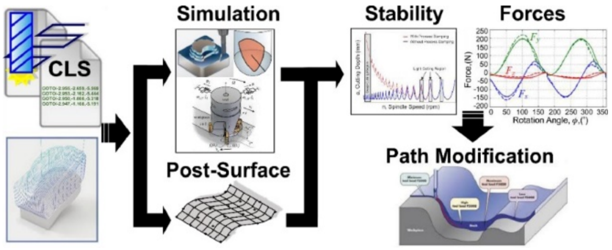


Fig. 4. Decision approach for chatter avoidance tool path modification [26].

used to show alarm for roughness with accuracy of 85 % [23]. Unsupervised learning approach was also attempted. Dynamometer signals from end milling thin-walled parts were unlabeled and compressed by a deep autoencoding process. Then hybrid clustering based on density and distance metrices was used on the compressed signals to detect chatter with accuracy of 95 % [24].

With the AI models having shown ability to see vibration from the standalone conditions, there is also research into the applicability of transfer learning to see whether the ability can be maintained when the cutting condition changes. Yesilli et al. [25] separately applied wavelet packet transform (WPT) and ensemble empirical mode decomposition (EEMD) to data from an acceleration sensor placed on the toolholder of a lathe. The two methods were combined with support vector machine (SVM), logistic regression, random forest (RF) classification, or gradient boosting, through recursive feature elimination. Transfer learning capability was tested by operating in other configurations with varying stickout length. It was found that when the configuration stayed the same, WPT and EEMD can each achieve accuracy reaching as high as 94 % and 95 %, respectively; when the cutting condition changed, EEMD was found to outperform WPT with accuracy reaching up to 95 %.

The results of chatter prediction can be used for machine optimization. The self-optimizing developments for chatter consideration are introduced. Tunc [26] described an optimization technique for a five-axis milling process for the purpose of avoiding chatter, while also considering cutting forces and scallop height. For stability consideration, variable cutting depth was implemented, which also reduced cycle time. The decision workflow is shown in Fig. 4. The optimization was concerned with tool path generation. Stock shape, stock dimension, and tilt angle can also be adjusted to increase stability [27]. Chao et al. [28] similarly updated tool orientation for the purpose of chatter-free conditions in five-axis ball end milling. Yuan et al. [29] used historical displacement information from a laser sensor in three-axis milling operation to train a Bayesian network. Then a predictive controller is developed to mitigate vibration while also taking into account deformation of the workpiece by setting depth of cut.

Although analytical physics models have been made to relate machining stability to the process parameters, they contain many assumptions and conventionally do not consider nonlinearity effects. AI models have shown the potential to overcome these limitations and to predict complex behaviour accurately. Opportunities exist to further extend the models to include automatically identifying dynamic parameters using AI. On-line chatter detection has also been explored, and the results can be used in the process optimization in real time by changing spindle speeds or cutter position. More sensor technologies in addition to the conventional force sensors are experimented with to enable this function, with signal processing AI algorithms and recognition. In addition to changing the process to suppress vibration, active damping or stiffener are also being experimented with at the cutting tool or toolholder.

Since chatter stability is affected by many factors, a successful algorithm in one operation might not be successful in another operation. This creates the issue of transferability explained in more detail in a later section that needs to be addressed in order to ensure practicality. Self-optimizing mechanisms and AI approaches have shown ability to recognize chatter, and opportunities of enhancement and integration ideas for further research.

3.2 Error measurement and compensation

With the increasing demand for high accuracy of machine tools, several researchers investigated error compensations. Accuracy is affected by error sources during the machining process [30]. There are several error sources such as geometric, kinematic, thermal and tool wear, etc. One of the principal factors of the inaccuracy in machine tools is thermal error caused by the thermal deformation [31, 32]. This accounts for 40~70 % of inaccuracy in the machine tools. Thus, it is essential to reduce thermal deformation error for precise processing. Also, mitigating high temperature can improve tool wear. In general, there are two types of heat sources in a machine tool structure, an internal source generating heat inside the machine and an external source generating heat with the surrounding environment. In order to minimize these thermal errors, various methods have been proposed such as thermal error avoidance, thermal error control, and thermal error compensation. Among them, thermal error compensation is the more effective, convenient and cost-efficient method.

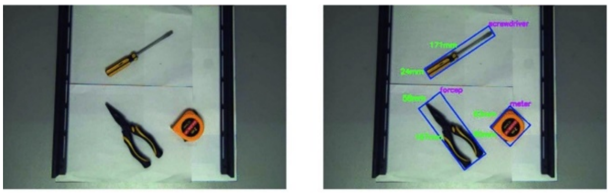
Thermal compensation is a method that adjusts the position of a machine's axis by an amount equal to the thermal error at a particular time. For measuring the temperature and thermal error values, temperature sensors and displacement sensors are usually used to collect the data [33]. Variations of temperature are measured by temperature sensors and thermal deformation data is collected through the deformation sensors on the spindle and overall frame of system. Selection of the appropriate sensors is also important, but it is essential to efficiently locate the sensors and select the number of them. Therefore, there are a few ways to improve accuracy by utilizing methods such as fuzzy clustering for proper thermal sensor selection [34]. A large number of temperature sensors are needed to cover the entire machine tool system and structure. Based on the data collected from the sensor, the thermal state of the machine tool is monitored. The overall conditions of the machine are verified in real-time, and the thermal compensation scheme is adopted during the machining.

Despite many efforts using theoretical thermal models, they may not be accurate enough to provide sufficient information on the boundary conditions of the machine tool and the heat generation rate from various machining conditions. The relationship between the thermal error and temperature field is nonlinear. AI models can learn complex nonlinear relations and efficiently process inaccurate data. It can increase the accuracy and improve the limitations of existing models. Therefore, several researchers have been investigating prediction models for thermal errors in machine tools using empirical model structures with an AI method. Thermal error compensation has been implemented mainly by applying compensation values computed online via a thermal error model to machine tools in real-time. The error compensation value is obtained by using a regression method/AI algorithm based on the acquisition of sensor signals for verifying the thermal deformation and calibration origin of machine tools during the machining process. Fujishima et al. [35] proposed a novel thermal displacement prediction and virtual compensation method in turning using convolutional neural network (CNN). The method considered ambient temperature change, and heat generation from cutting, spindle rotation and axes movement. For changing the compensation weight adaptively, reliability evaluation based on Bayesian dropout was used in thermal displacement prediction. Different types of ANNs have been developed for thermal error compensation modeling such as cerebellar model articulation controller (CMAC) [36, 37]. Yang et al. [36] proposed a CMAC neural network algorithm that systematically learns to search for the characteristics of nonlinear interactions between the thermal errors and temperature area on the structure. Ma et al. [38, 39] also improved the accuracy of their model by using particle swarm optimization (PSO) with backpropagation (BP) neural networks. By thermal compensation based on this model, the dimensional error was reduced and the surface quality was improved. Li et al. [33] developed a thermal error prediction model for a spindle system using improved particle swarm optimization (IPSO) with a back propagation (BP) neural network to improve the low accuracy and poor convergence of the BP model. The IPSO-BP prediction model increased the prediction accuracy and had better generalization ability. The grey neural network model was proposed to improve the prediction accuracy of grey system models since conventional models that consist of the least square method were not suitable for solving the nonlinear thermal errors problem [40-43]. Liu et al. [44] used a four-stage framework that included bidirectional long short-term memory (BiLSTM), feedforward neural network, and max pooling, to model thermal error in horizontal milling. The model framework was used for compensation, in which the depth variation due to thermal error was reduced by 85 %. Chengyang et al. [45] proposed a novel multi-classification CNN model of spindle thermal errors, unlike the traditional empirical model. The thermal image was used for predicting spindle thermal errors. It shows 90~93 % prediction accuracy and is higher than that shown by the fully connected BP neural network.

Recently, various research has been proposed about error prediction and compensation based on the digital twin. It is a challenge to predict the error for a certain machining when the machine tool and numerical control (NC) program are determined. Liu et al. [46] proposed a method of the time-varying error prediction and compensation for the movement axis of the CNC machine tool based on the digital twin, which was built from heat transfer theory. The framework is the combination of digital twin of milling grooves and holes, and time-varying error compensation, and the 3D real-time presentation for the thermal deformation of the movement axis is created. Then, it can predict the time-varying error for the movement axis in the future machining. Liu et al. [47] proposed a digital twin system of thermal error control for a case of grinding a large-size gear profile. The digital twin system was developed using a new cloud-haze computing architecture. A gated recurrent unit (GRU) optimized by a bat algorithm was embedded in the model, and was trained with data fed from temperature and position sensors placed around the machine. It can solve the serious problem of the efficient processing of large-volume data in the industrial internet environment that has characteristics such as limited bandwidth and latency.

Dimensional errors of the machined part cause problems such as inability to assemble, quality deterioration, and vibration of the product after assembly. Also, dimensional errors due to inaccurate measurement of the workpiece before machining can affect tool wear and lead to reduced tool life. Traditional methods of dimension measurements are manual measurements using tools such as vernier caliper, tape measure or micrometer. Though the traditional measurements are simple, they require additional time and labor for measuring, and accuracy of measurement is affected by the workers. Nowadays, digital image processing technology can be used to measure dimensions of objects. A non-contact dimension parameter measurement system was realized using machine vision and image processing [48]. Machine vision and image processing were used not only to measure the dimension of products, but also to improve the accuracy of measuring physical defects such as cracks. A method to improve the accuracy of crack length measurement based on machine vision was proposed [49]. As digital image technology was applied to measurement, the images were utilized in AI algorithms to measure dimension. In addition, AI algorithms based on convolutional neural networks (CNN), which are most suitable for using images, were mainly used to measure dimensions.

A dimension measurement system of objects using deep learning with digital images was developed [50]. They used the mask region based convolutional neural network (CNN) to detect all objects to be measured and distinguish segments for each object on images from the camera. To get the two-dimensional sizes of objects, they used digital image processing to extract the edge contours of objects for obtaining minimum bounding rectangles of the objects. The advantage of a



(a) (b)

Fig. 5. (a) Original image of objects to be measured; (b) result image of object dimension measurement [50].

measuring system based on AI is that it can measure several objects in a short time, which can improve productivity. But a challenge is that image processing technology is needed to measure the dimensions of an object. Also, the measurement is limited to the resolution of image. Fig. 5 illustrates the vision-based measurements using AI.

Predicting machining quality and errors can replace the measurement process. It can reduce the process time and the effort for measurement, so productivity improvement can be expected. Surface roughness is the major index of the product quality. Traditionally, surface roughness is measured using a form tracer system by contacting surfaces using a stylus, or a 3-dimensional measurement system machine using a microscope. Recently, to reduce additional processes for measuring surface roughness, the surface roughness is predicted through the AI method. Adaptive network-based fuzzy inference system (ANFIS) can be especially useful to deal with nonlinear mapping. Thus, ANFIS is considered a suitable AI method for prediction of surface roughness. ANFIS was applied as a model to predict surface roughness in end milling using parameters such as spindle speed, feed rate, and depth of cut [51]. A system to predict surface roughness for the end milling process using ANFIS was developed [52], and a hybrid Taguchi-genetic learning algorithm (HTGLA) was applied in the ANFIS to determine the suitable membership functions and optimal parameters to investigate the effectiveness of predicting surface roughness. The machining parameters such as spindle speed, feed rate, and depth of cut in end milling were input variables of the ANFIS and surface roughness was output variable of the ANFIS. The HTGLS-based-ANFIS were trained by directly minimizing the root-mean-squared-error (RMSE) criterion. This HTGLS-based-ANFIS showed 4.06 % prediction error of the surface roughness compared with the actual experimental results.

With the number of machine learning methods available, there was research into comparison of the methods for prediction performance. Jurkovic et al. [53] developed three models and compared their performances at prediction of operating parameters in the case of high-speed turning. The parameters included surface roughness, cutting force, and tool life. Polynomial (quadratic) regression, support vector regression, and an artificial neural network were used. They found polynomial regression to have the best performance for roughness and force prediction, while ANN had the best performance for life prediction.

An evolutionary neuro-fuzzy system for evaluation of surface roughness that consisted of three units: cutting parameters (first unit), optimization of cutting parameters for minimizing machining time and maximizing metal removal rate (second unit), and control of required surface roughness by means of the features quantified from digital images of the machined surface (third unit) was suggested [54]. In the first unit, input variables of ANFIS were the basic face milling cutting parameters: spindle speed, feed per tooth, and cutting depth. In the second unit, a genetic algorithm (GA) was applied for optimization of the cutting to minimize machining time and maximize metal removal rate while maintaining required surface roughness. After the experiment, digital images of the machined surfaces of all samples were taken by table scanners. All digital images were inscribed in matrix form, and in matrix form the three variables: the mean value of the columns matrix, the standard deviation of the columns matrix, and the ratio were used as input values of the fuzzy inference system for evaluation of surface roughness. A fuzzy logic-based supervision controller was developed for real-time adjustments of cutting parameters like feed rate and spindle speed for achieving desired surface quality [55]. A neuro-fuzzy prediction model was used to estimate the surface roughness by using real-time input of machining parameters (feed rate and spindle speed) monitored via smart sensors attached on CNC machines. The case study conducted milling of steel alloy to validate research. The case study showed the surface quality was improved with adjustment by the supervision controller. Initial exploratory testing of the concept of digital twin in regards to position error has been done with a CNC motion test bed. A flexible drive shaft with non-linear backlash and friction was considered in the virtual representation which included mechanical and electrical components. Simulated annealing (SA), genetic algorithm (GA), and cross-entropy (CE) method were separately utilized for optimization of the controller based on the digital twin, and accounted for the backlash peak amplitude, backlash peak time, and hysteresis amplitude. The strategy improved the position error on the test bed, by having the digital twin interact with an open CNC, where the cross-entropy method was found to have the best performance of the procedures [56].

The AI methods used in terms of thermal and dimensional errors in machine tools were investigated. In thermal error measurement, a temperature sensor or infrared thermal camera is used to measure the temperature variation of the system, and data of thermal error is collected using displacement sensors. Based on the collected data, the prediction model for compensation can be developed and thermal error compensation is conducted based on the modeling. Since the data between thermal error and temperature fields are nonlinear, modeling with AI methods is efficient in developing models for these complex nonlinear data. The thermal error compensation by applying an AI method is more accurate than existing models. For dimensional measurement, CNN-based AI measurement through machine vision was introduced, and productivity can be improved by being able to measure several objects at once using an AI method. However, there is a limitation of minimum unit of measure due to the limit of the resolution of measuring devices such as cameras. For prediction, ANFIS algorithms that predict surface roughness were introduced. Accurate prediction is possible, and they are also used in applications such as real-time monitoring. However, it is necessary to conduct an experiment for AI training, and there is a limitation in that experiment must be conducted whenever the workpiece or tool is changed.

3.3 Process optimization

The selection of machining parameters is crucial to determine the success of machining operations. The parameters are traditionally selected by the operator's judgement and experience or following handbooks. However, the selected machining parameters usually do not provide an optimal result because of a number of factors that interrupt achieving accuracy and high productivity.

In the recent trend of machining parameters optimization, AI has been used to find the optimal feed rate, spindle speed, depth of cut, etc. for minimizing the surface roughness. The AI technique has been applied in developing a predictive model and optimization. Since the development of an accurate predictive model is essential to optimize machining parameters, researchers have developed a dynamic-based model using the friction models. In contrast to this theoretical modeling method, the AI technique is the data-driven modeling approach. For example, a predictive model can be developed using an ANN [57]. The machining parameters such as cutting speed, feed per tooth, depth of cut, and flank wear were inputs to the model, and the predicted surface roughness was its output. The predictive model is then used to optimize the machining parameters using a genetic algorithm (GA) to have the minimum surface roughness. Milling process planning and scheduling was optimized to improve energy efficiency and productivity with high surface quality [58]. The paper proposed a two-stage optimization approach: (1) Optimization of machining parameters using ANNs, (2) Optimization of process sequence, set-up and schedule using pattern search, genetic algorithm (GA), and simulated annealing algorithm. ANN has also been setup for the process of roller burnishing, to map the nonlinear relationships between feed rate, burnishing force, roller contour radius, surface roughness, and strain hardening. Genetic algorithm (GA) was used in the trained model to find the fastest feed rate while maintaining the desired surface qualities [59]. These data-driven modelling approaches have an advantage in terms of finding the relationships between system state variables (input and output) without prior knowledge of the system. Through training an algorithm (e.g., linear regression, ANN, Gaussian process) on manufacturing data, the data-driven models can derive the system's relationship. One drawback of the data-driven model is that the model's reliability is determined by data quality. This challenge, described in more detail in a later section, shows that it is important to prepare a suitable data set for modelling the desired system in the machining process.

Intelligent controls such as neural networks, machine learning, reinforcement learning, fuzzy logic, genetic algorithms, and evolutionary computing have been applied to improve the surface quality in real-time. For example, an ANN observer was used in a controller to control the cutting parameters [60]. By integrating with the surface roughness predictive model from a multi-layer perceptron (MLP), the AI controller helped to achieve the desired surface roughness. With proportional integral (PI) sub-controllers, rule-based fuzzy logic controllers (FLC) were also used to improve the surface roughness in a closed-loop control algorithm [55].

AI techniques have also been used in both an off-line optimization module and surface roughness control [61, 62]. The basic idea of the offline optimization approach was to merge the particle swarm optimization (PSO) algorithm and neural network (NN) based cutting force model. The cutting force model generated a 3D surface of cutting force, then used this surface to find the optimal feed rate and spindle speed using a PSO algorithm. In surface roughness adaptive control, there were a feed drive model, a spindle speed drive model, and five basic prediction models of machining quantities. These prediction models were: reference force model M1, feed rate control model M2, spindle speed control model M3, NN based cutting force model M4 and ANFIS surface roughness model M5. Fig. 6 describes these prediction models with controller. These intelligent control approaches have an advantage in terms of providing better control performance without depending on models beforehand. The controller learns from training data so it can self-tune until a satisfactory result is reached. It can also adapt to changes in the conditions in the environment with less interference by a human. However, most intelligent control schemes are hard to implement into a system. Without proper knowledge about the controlled variable, system, input, and output, the controller cannot work or cannot determine if it is working correctly. Sufficient training data is also required. These challenges need to be overcome in order to use intelligent control in the machine process.

The tool path optimization is also important for productivity and accuracy. Artificial immune systems (AIS) were proposed in the tool path generation problem for the non-uniform rational B-spline (NURBS) surfaces [63]. Since there are many points and NURBS equation variables, AIS optimization algorithm is used to avoid possible local optima and to get to the desired solution in an iterative fashion. The novelty is to apply the AIS approach on both the u and v parametric directions in order to compute the tool path interval for ball-end milling. A geometric simulator, a physical process model, and a machining parameter optimizer for 2 ½ axis end milling was developed and integrated by using a commercial solid modeler (ACIS) and ANN technique [64]. The geometric model created by using ACIS can simulate the milling operation to extract the critical in-cut geometric information between the cutting tool and the workpiece. A radial basis function (RBF) neural network was im-

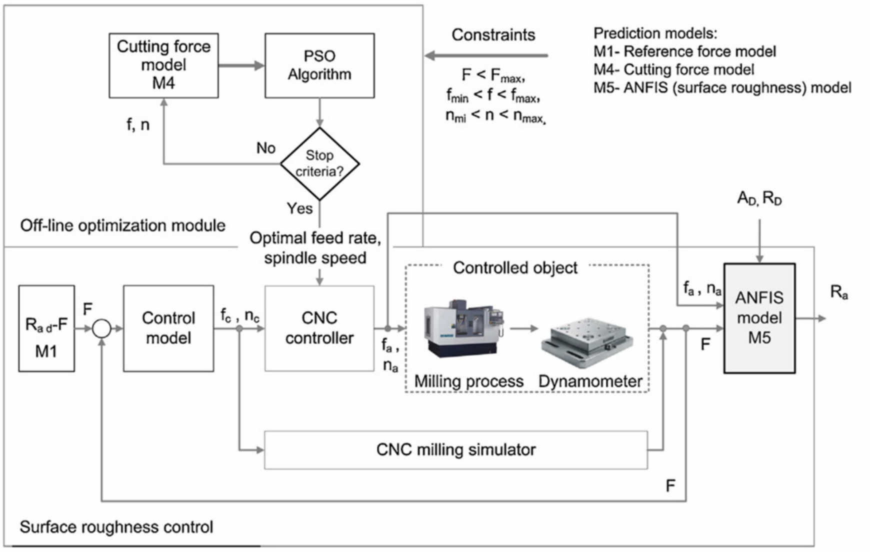


Fig. 6. Block diagram of the surface roughness control simulator [62].

plemented to develop the physical model and to optimize machining parameters for maximal production, minimum cost, and maximal surface finish. The optimized parameters were used to reschedule NC code. Neural networks (NN) were also used to predict the milling path strategy or the sequence of the milling process [65]. These models were used to train the NN using the input data to predict the milling path strategy that produced the best surface quality. An ant colony optimization (ACO) was used in a traveling salesman problem (TSP) to optimize hole-making operations in order to reduce machining time and to improve productivity of the manufacturing [66]. Similarly, the ACO algorithm was used to find the optimum path planning in CNC drilling machines for a large number of holes [67]. To create smoothing of discontinuous tool paths for higher efficiency, a deep neural network was constructed which outputted servo commands, and was trained with reinforcement learning [68]. The model contained features such as input tool path, error constraint, current position, etc. Current status and rewards were used to train the model, with training algorithms of Q-learning, state-action-reward-state-action, deep deterministic policy gradient, etc. separately used. The method could achieve real-time performance and thus could be applied to real CNC milling.

The use of AI allowed for prediction of machine tool conditions and therefore, the appropriate optimization of machining parameters. The data-driven approach helped to circumvent the complex relations between multiple parameters, which is difficult to calculate all at once analytically, in order to provide an optimization with all the considerations. As well, AI approach has been used to suggest tool path strategy, for the purposes of enhancing yield and workpiece quality.

3.4 Energy consumption management

The energy consumption of the manufacturing industry has become one of the key considerations due to rigid intergovernmental environment policies such as long-term low greenhouse gas emission development strategies (LEDS), reduction of plant operating energy cost, and demand for energy-saving equipment. Considering energy consumption of machine tools, a lot of energy optimization or energy efficiency improvement research has been done in two ways: optimizing or developing additional programs into the main and support units of the machine tool which can control the energy-saving system, and operational efficiency measures such as process parameter adjustment through energy empirical model, energy flow map and machine learning (ML) model for energy saving [69].

Current efforts in the real industrial field focus on saving the energy of machine tools by developing programs into the main and support units of machine tools. For example, Okuma ECO saves energy by reducing the machine operating and idle time power consumption [70]. The intelligent control could reportedly save energy up to 74 % by stopping machine tool idling. Similarly, other machine tool manufacturers use a machine control interface that can turn off the power when not in cycle based on the machine idling time. Such techniques and programs involve just stopping unnecessary operation of the machine tool or monitoring the operation status.

To save energy more efficiently, many researchers are using data-driven approaches which could save more energy and improve efficiency by estimation of energy consumption. The first step towards reducing energy consumption of machine tools is to understand their energy consumption [71]. Due to varying definitions of energy consumption of machine tools, there are various theoretical models [69]. Zhao et al. [72] classified an empirical model during cutting. At the process level, net cutting specific energy, which is energy consumed in actual material removal, is influenced by process parameters and material properties. Sihag et al. [73] defined six hierarchical classification criteria of machining energy in machine tools.

They provided comprehensive information at the first level and went down to specific information at the sixth level. In the first level, energy consumption can be divided into three components: machine tool, spindle, and process. At the process level, the energy consumed for actual material removal is the output, and chip formation and surface generation are affected in energy consumption of the process level. Therefore, the energy consumption is considered with the process parameter to get appropriate cutting energy or a predictive model of cutting energy consumption with higher performance. The energy consumption prediction helps in determining optimized parameters to save energy, but large amounts of experiments are needed to determine the coefficients for empirical models.

Kant et al. [74] developed an accurate predictive model of cutting energy consumption using ANN during a milling process through comparing the experimental results and analyzed the influence of machining parameters such as spindle speed, feed rate, depth of cut, and width of cut on cutting energy. Zhao et al. [75] developed a backpropagation neural networks (BPNN) prediction model for specific energy consumption which meant the required energy consumption for cutting unit volume material. Using the comparison of mean square prediction error, the highest performance structure was adopted. Zhang et al. [76] improved the ability of hybrid ensemble neural networks model for forecasting electrical energy consumption of a non-linear grinding process and made the robust forecasting performance. Liu et al. [77] proposed the hybrid prediction model of future energy consumption based on empirical mode decomposition (EMD), least squares support vector regression (LSSVR), and quadratic exponential smoothing (QES) for a cement grinding process. This hybrid model is compared with other models by root mean square error (RMSE) and mean absolute percent error (MAPE), and results proved the high performance of the future energy prediction model. Ak et al. [78] proposed a neural networks (NNs) ensemble prediction model which can predict the interval for energy consumption of milling machine tools during face milling operations by using the input data and a regression model. The proposed prediction model showed high prediction interval coverage probability (PICP) with smaller normalized mean prediction interval width (NMPIW) than individual NN training.

Theres was also comparison made on different AI approaches for energy consumption prediction of cutting process. Xiao et al. [79] used the deep learning setups of convolutional neural network (CNN), stacked auto-encoder (SAE), deep belief network (DBN) separately to model energy consumed in turning process, and compare to support vector machine (SVM). Input data such as workpiece diameter, hardness, cutting length, etc. were acquired. K-fold cross-validation was used to assess the methods, which found that the deep learning methods had higher accuracies than SVM.

The energy consumed by the entire machine tool such as control systems, drive systems, cooling and lubrications units, and spindle motor, was considered. Zhang et al. [80] proposed an integration of process planning and scheduling (IPPS) model based on nonlinear process planning (NLPP) to implement energy-saving methods and predict the energy consumption of machine tools in product manufacturing processes in machining systems using a Therblig-based model. Then, the optimal process plan and energy saving effectiveness of IPPS was verified by the case study comparing a genetic algorithm (GA)-based approach applied with process planning and scheduling work independently. Flum et al. [81] developed a simulation model, which could breakdown a turning machine, to predict energy consumed by various components in the machine. Real machine tool input data was used with Mathworks Simscape™ to establish the virtual module. Sets of simulated data were compared with measured data on the physical hardware in the different situations of standby, ready, and work, and the deviation were found to be within 10 %. It represents an attempt in building digital twin model where different NC code strategies could be simulated considering energy efficiency.

In the AI aspect, most of the algorithms used are neural networks for energy conservation. The appropriate AI selection for machine tool energy consumption is still challenging since they may fall into local minima rather than global minima values. Recently, prediction models with AI to diagnose abnormal states of spindles in machine tools have been researched, but this diagnosis based on energy consumption needs to be expanded to machine tool systems including the cooling, idle, etc.

3.5 Tool condition monitoring

Reliability and availability of machines play an important role in decreasing production costs and time, as well as increasing accuracy. Proper machinery maintenance is required to maximize the reliability of the manufacturing process. Based on the European Standard of EN 13306, maintenance can generally be categorized into two groups i.e., corrective maintenance and preventive maintenance [82]. The former is carried out when a failure or fault is detected in the system and includes deferred corrective maintenance and emergency (or immediate) maintenance. The latter includes time or age-based maintenance (or predetermined maintenance) and condition-based maintenance [82, 83].

Interventions ahead of time, which normally impose unnecessary significant costs to the manufacturers, can be averted using condition-based preventive maintenance. Diagnostics and prognostics are two methods of condition-based preventive maintenance [84], and they are both included in prognostics and health management (PHM) of a system [85]. Diagnostic is defined as the process of detecting all existing faults and failure modes in the system, while the process of predicting future states and remaining useful life (RUL) is defined as prognostics [85-87].

Fig. 7 illustrates the different maintenance strategies. Elattar et al. [88] categorized the prognostics approaches into four types: (a) Reliability-based (or experience-based) prognostics, which is appropriate for unmonitored mass productions, de-

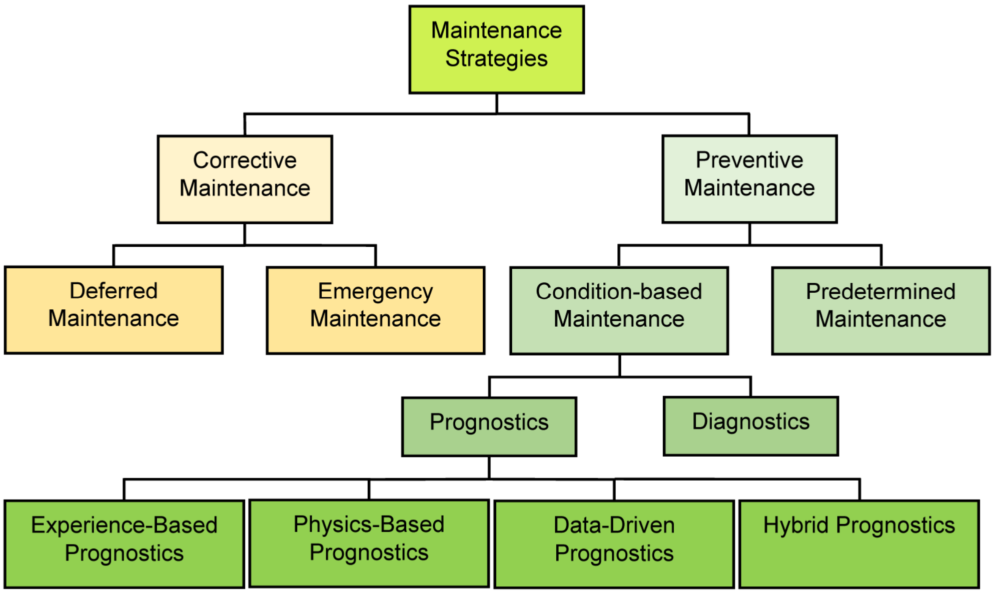


Fig. 7. Maintenance categories [82, 88].

pends only on the historical data about the same component and its average rate of failure; (b) Physics-based prognostics, which uses the mathematical models for the system's failure or degradation, is very accurate, and descriptive. However, since detailed knowledge about the system and operating parameters is required for an accurate modelling, this strategy can be very costly and time-consuming; (c) Data-driven prognostics, which relies on techniques from AI, uses the parameters of the systems that can be constantly measured to develop a model that correlates the variation of the measured parameters to the degradation level of the system. This method is cost-effective and quick, although its accuracy, which depends on the quantity and quality of the available data, could be less than the physics-based prognostics; (d) Hybrid approach, which is also called the fusion approach, is practical when at least two of the mentioned approaches are available. It combines these methods to tackle the limitations of each one [89]. Especially when both the physics-based and data-driven models are available, the hybrid approach can lead to very accurate results [90].

In machining operations, tool condition monitoring (TCM) is essential to achieve high dimensional accuracy and surface quality while also preventing tool failure and decreasing downtime. Tool wear, which continuously progresses, affects the surface quality of the machined workpiece, and in the worst case, it can cause a catastrophic failure. If the tool is monitored constantly to detect excessive tool wear, the cutting parameters can be tuned to optimize the tool life [91, 92]. Monitoring the tool wear can be categorized into two different methods [93-95]; the first one is the direct method (or offline method) which relies on the visual checking of the tool using CCD cameras, optical sensors and a laser scan micrometer, or measuring the electric resistance between tool and workpiece. This method can provide accurate information about the tool state.

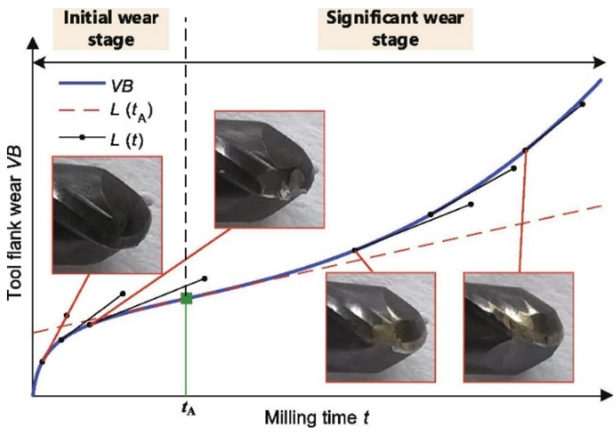


Fig. 8. A typical tool flank wear curve in milling with different wear conditions [96].

However, the main limitation of this method is the interruptions needed to check the tool which have an adverse impact on the production time. The second one is the indirect method (or online method) which uses the data gathered by different kinds of sensors to estimate the condition of the tool. The latter method can be used to predict the remaining useful life (RUL) efficiently during the machining process without any interruptions if an appropriate PHM system is developed in addition to monitoring the tool state continuously.

In order to predict the RUL of a component using data-driven prognostics, multiple sets of run-to-failure data are needed to model the degradation. For TCM, generally, flank wear is monitored and considered as a sign of degradation. A typical flank wear-time curve is shown in Fig. 8 [96] which also depicts the initial wear stage and the unhealthy stage. In this model, t_A is time when the curve changes from concave to convex. After

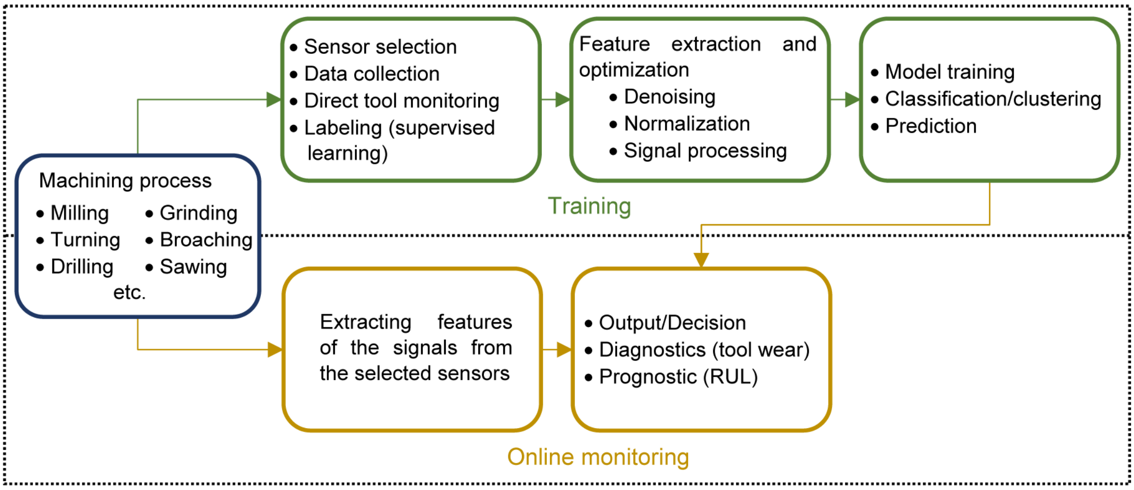


Fig. 9. Different steps in the TCM process.

extracting the flank wear-cutting time curve, the lifetime is divided into different health stages and an appropriate health indicator (HI), which represents the health state, is considered for the degradation trend [97]. Lei et al. [98] categorized the HIs into two groups i.e., Physics HIs and Virtual HIs. The former HIs are generally extracted using statistical or signal processing methods. These HIs are related to the physics of failures. However, if the HIs are extracted from the fusion of multi-sensor signals, it is hard to determine their physical meaning and they just represent the degradation trend of the system virtually [89, 98, 99]; hence, they are called Virtual HIs.

Data-driven-based TCM is gaining more and more attention, as it is time and cost-effective. As shown in Fig. 9, there are three important steps in data-driven based TCM i.e., sensors selection, feature extraction and, training and decision-making method which will be discussed in the following sections.

The first step for the data-driven prognosis approach (also called data mining or machine learning) is selecting and measuring the parameters whose features can correlate well with the degradation of the system. For the TCM, these parameters could be cutting force, acoustic emission, sound, vibration level, temperature, and motor current. When the tool gets dull, the friction between the workpiece and the cutting tool increases the cutting forces and the temperature of the tool (or the workpiece). The cutting forces can be measured directly, e.g., using multicomponent dynamometers or indirectly estimated if the motor current is measured during the process using Hall effect sensors. The temperature is normally measured using contact methods by embedding thermocouples or non-contact methods by infrared thermography (IRT). The variation in tool conditions can also affect the vibration level [100]. The signatures of vibration signals such as mean, RMS, and peak to peak, increase with the tool wear [101]. Based on that, vibration sensors such as accelerometers and laser vibrometers have been used for TCM. Furthermore, acoustic emission (AE) and sound signals are also very popular for TCM because they are highly related to the tool condition and they propagate at very high frequencies which are distinguishable from the cutting frequencies [102]. Teti et al. [103] and Kuntoğlu et al. [104] have reviewed the merits and demerits of using each of the above-mentioned sensing systems for TCM.

When the signals are acquired, it is important to extract the most suitable features which are independent of cutting conditions and correlate well with the tool wear. These features can be extracted in time domain using time series analysis including auto-regressive (AR), moving average (MA) and auto-regressive moving average (ARMA) along with statistical features such as maximum to minimum ratio, average value, root-mean-square (RMS), skewness, standard deviation, and kurtosis [94, 103], in the frequency domain using the fast Fourier transform (FFT) to extract the spindle and tooth pass frequencies, peak to peak amplitude and the power spectrum [105], or in time-frequency domain e.g. using wavelet analysis. Frequency domain features have the advantage over the time domain features that the parameters can be easily separated for the important frequencies such as spindle frequency or tooth passing frequency [106]. Continuous wavelet transform (CWT), discrete wavelet transform (DWT) which is faster than the CWT [94], wavelet packet transform (WPT) which has better frequency resolutions on high-frequency band signals than the DWT [94], complex continuous wavelet transform (CCWT), Hilbert transform (HT), and empirical mode decomposition (EMD) are some of the signal processing techniques to extract time-frequency domain features [94, 105].

Selecting the appropriate feature of the signal depends on some parameters such as the type of the sensors used to monitor the tool. For force sensors, generally, time-domain features are used while for vibration, sound and AE sensors frequency domain features are more common [104]. However, since the signals captured during machining processes are generally non-stationary, the time-frequency features are more favorable [107]. Moreover, using the time-frequency domain, the features from both perspectives were investigated.

After extracting the suitable features of the signals measured from the experiments, the tool condition should be estimated using decision-making algorithms. Several methods have been used for this purpose including ANN [108], probabilistic neural network (PNN) [109], convolutional neural network (CNN) [110], recurrent neural network (RNN) [111], neuro-fuzzy systems [112], adaptive neuro fuzzy inference system (ANFIS) [113], fuzzy clustering [114], regression [115], fuzzy logic (FG) [116], genetic algorithms (GA) [117], support vector machine (SVM) [118], support vector regression (SVR) [119], the hidden Markov model (HMM) [120], decision trees [121], and extreme learning machine (ELM) [102]. Among these methods, ANN, HMM, and SVR are more popular for TCM [94].

Gouarir et al. [110] used experimental data which was obtained from a force sensor monitoring wear progression of the tool flank to train a convolutional neural network (CNN), after which the network could relate the cutting forces to the tool flank wear. This was tried on milling of stainless steel, with a non-coated ball endmill, in dry machining conditions. The network can then be used for wear prediction purposes. Extreme learning machines (ELM) were used to speed up learning and improve accuracy. Laddada et al. [122] evaluated the health condition of the cutting tool and estimated the RUL based on complex continuous wavelet transform (CCWT) and improved extreme learning machine (IELM). In order to gather the data, they conducted different run-to-failure cutting tests using a CNC machine to train their model. Zhou et al. [102] used different dimensional and dimensionless statistical features in time and frequency domains from a single sound sensor placed near the workpiece. First, the features were extracted from sound signals while cutting tools with different known normal and wear states were used to train the two-layer angle kernel extreme learning machine (TAKELM) model. Then the model was used to predict the wear of some tools with unknown conditions. They reported that the prediction error in the TAKELM method was much less compared with KELM and least square-SVM with an insignificant increase of the computation time compared with the KELM method. In order to increase the accuracy of the predictions, Luo et al. [123] attempted to fuse theoretical and data-driven RUL estimation of milling tool in a digital twin model, that had degradation mechanism, material characteristic, and operating conditions as the basis. They established a multi-domain model of coupled dynamics and thermodynamics to simulate the temperature, stress and relative slip speed during milling which were used to calculate the tool wear. The predicted values from simulation and data-driven approaches were fused in a particle filtering algorithm. The hybrid approach yielded more accurate results compared to each of the single approaches in their investigation.

Tool wear monitoring methods have been also studied for other traditional machining processes such as sawing [124], broaching [125], and grinding [126, 127]. Caesarendra et al. [126] used a 10-layer CNN to predict the belt grinding tool wear in polishing processes using a 3-axes accelerometer and a table dynamometer. They studied the different combinations of signals in three axes and reported that some combinations provide more accurate predictions of the tool state than the others. Oo et al. [127] also proposed a tool wear monitoring model for belt grinding using image-processing techniques. In their model, a random forest classifier (RFC) and a multiple linear regression (MLR) were combined to detect the current state of the tool and to predict the RUL.

Although the majority of the articles for TCM are based on supervised training, few models have been developed for unsupervised learning. Since the tool wear gradually propagates until the failure, Kumar et al. [128] used unsupervised learning for temporal clustering of unlabeled data. They utilized HMM to perform a model-based clustering and considered that the tool was perfectly healthy at the very beginning and it failed at the end (run-to-fail dataset). Then they developed a prognostic module based on the results of diagnostics using a polynomial regression model. Dou et al. [129] developed an unsupervised model for online monitoring of tool wear using a sparse autoencoder (SAE). In their model, the features of the force and vibration signals were extracted adaptively for training without supervision of the empirical label.

One of the most important challenges for TCM is that the online monitoring of tools usually requires multiple expensive sensors and relevant equipment such as amplifiers and data acquisition systems. Moreover, there are some restrictions on the size and material of the workpiece to utilize some of these sensing systems. For example, it is not very practical to constantly use piezoelectric table dynamometers in a workshop to measure the cutting forces during the machining of components with different geometries.

Most of the developed models in the field of TCM are diagnostic-based which means they are capable of evaluating the current state of the tool including the tool wear condition and other faults of the tool. However, prognostic-based models, which estimate the RUL of the tool, would be more beneficial in industrial settings because the qualitative classification of the current tool wear condition cannot provide accurate information about the future state of the system.

Moreover, the developed models are sensitive to cutting parameters. Hence, these models may result in inaccurate tool condition estimation if the machining conditions are different from what the model is trained for, and they cannot be generalized for various cutting conditions [96]. Most of the developed algorithms were trained and verified for a specific condition, e.g., tool material and geometry, workpiece material, and cutting system dynamics. Although most of them were trained well to predict RUL or state of the cutting tool, they might produce unreliable results for the conditions different from the training ones. Moreover, the system dynamics might be different from one machine to another, and it is also dependent on the position of the sensors. Hence, it is important to consider the dynamics between the applied force on the tool tip and the sensors in the training models. Hybrid prognostics which utilize the physical model in addition to data extracted by the sensors can be used to overcome these limitations and improve the trans-

Table 3. Data quality problems.

Data quality	Phenomena	Possible solutions
Insufficient data	• Insufficient samples of the collected data set	Applying more sensors or generating virtual data using generative adversarial network (GAN)
Fragmented data	• Lack of some information in a data set • Referred to as 'missing data' problem • Mainly caused by inconsistent data collection systems	Data imputation methods corresponding to different types of missing mechanisms categorized as missing completely at random (MCAR), non-ignorable (NI), and missing at random (MAR) [133]
Biased data	• Significant difference in the amount of data between classes • Referred to as 'class imbalance' issue • Most frequently occurring problem in AI-based classification	Under/over-sampling of data (approaches at data level) or adjusting the weight values of minor classes in training process (approach at algorithm level) [134]
Imprecise data	• Inaccurate values measured and intermittent sampling delay • Caused by unstable and imprecise sensor systems	Reducing the sampling frequency, filling the empty section using interpolation methods, and synchronization in the data processing stage for different sampling rates

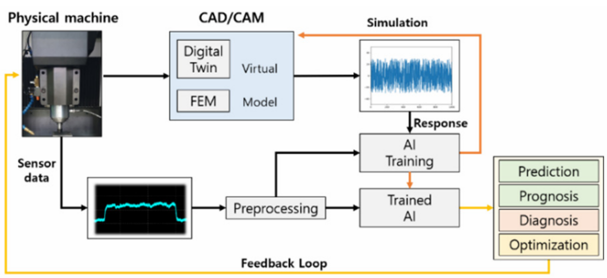


Fig. 10. Hybrid augmented intelligence in machining and machine tools.

ferability of the models on new environments considering the cutting conditions and dynamics of the systems.

4. Challenges and future outlook

Despite significant advantages associated with AI methods used in machining and machine tools, there are several challenges to overcome. With the many years of accumulated knowledge in machining and machine tool research, augmented intelligence is required in order to achieve the robustness and accuracy to harmoniously bridge human intelligence and AI. Fig. 10 illustrates the hybrid augmented intelligence capable of accurate prediction, prognosis, diagnosis, and self-optimization through the combination of digital twin and analytical models used for training. Physical sensor data can be also used to reinforce the learning process. A physical sensor network placed around a machine tool can provide data which can be used to build a real time model of the tool, workpiece, machining conditions, and in-situ metrology data. The loops complete integration between the physical machine tool, cyber space (virtual model), and human intelligence. The physical sensor data are preprocessed in order to address transferability between different machines. They can also be included in a database that stores the historical information and is ready to integrate with big data analytics, for instance, clustering to find relationship.

4.1 Data quality for AI

The most demanding and time-consuming process of applying AI is the preparation of an appropriate data set. As of 2016, it was suggested that a rough rule of thumb for a supervised deep learning algorithm is to have at least 5000 training samples in each category to achieve usable performance [130]. According to results of a survey of data scientists from Forbes, 80 % of the work for data mining and AI was related to gathering, cleaning, and organizing of data [131]. This issue is the major reason why there are insufficient ready-to-use AI applications for machining operations despite the continuous advancements in AI modeling. The inferior data quality can be classified into four types: insufficient data, fragmented data, biased data, and Imprecise data as illustrated in Table 3. For example of addressing data quality challenge, generative adversarial network (GAN) was investigated for increasing the data size to detect ball bearing fault with accuracy of 99.8 % [132]. Opportunities exist to apply the solution in smart machining to overcome the challenge with high accuracy, such as for detecting tool wear.

Although various solutions for the corresponding quality deterioration phenomena have been proposed, they are limited to addressing one or two factors, so the data quality issue is still the most challenging from the aspect of applying AI to poor data collection environments in industrial sites. Therefore, overall improvement efforts, from designing robust sensing systems to establishing the standards for data measurement, are needed in the future.

4.2 Transferability for AI

How well an AI trained for one machine performs on similar machines is the question that has been received great attention from industrial AI researchers, and this is known as transferability. Since existing AI models are highly dependent on mathematical features of the training data, if the value of the data changes for any physical reason, the AI reacts sensitively and outputs a dissimilar result. Even when machining is performed on the same workpiece on the same machine tool, AI is not guaranteed to operate consistently due to sensor data that varies depending on the machining conditions, dynamics and other environmental factors. Improving the transferability of AI is commonly approached at two levels: one at the data level and the other at the algorithm level.

At the data level, one can overcome this limitation predominantly through data scaling, including normalization or standardization. There are different types of scalers such as min-max, standard, max-absolute, robust, quantile transformer, power transformer, and unit vector, and it is necessary to select an appropriate scaler according to the distribution of data [135]. In order to implement efficient data scaling for improving the transferability, it is important to set specific information which does not change for different machines or systems in the same domain as a standard.

At the algorithm level, several techniques that make AI quickly adapt to similar domains with a small amount of data have been recently proposed, by subdividing the architecture of pre-trained AI models and allowing some to preserve existing training and some to retrain from new data. This kind of method is called transfer learning, and several studies have been reported that transfer learning was effective in AI modeling for fault diagnosis of mechanical parts [136-138].

Meanwhile, a hybrid approach incorporating digital twin has recently been proposed (see Fig. 10). The digital twin is a platform that interacts with various information by synchronizing with the actual system in a virtual environment and is being actively studied. If the digital twin is equipped with a physical model that works by the same mechanism as the actual system, it can be used as a reference for scaling data that is updated in real time. In other ways, modeling strategies for AI algorithms such as transfer learning can be developed using detailed operational information from digital twins synchronized to multiple machine tools.

4.3 Explainability for AI

As demonstrated, machine learning (ML) for machining operations meant that the models in subtractive manufacturing are moved away from physical models and towards probabilities. Therefore, the AI-enabled machine tool would often not have a rule-based model expert system which is more comprehensible to the user. Since the ways a human operator and machine understand the phenomena are different, it would be difficult to understand the reasoning behind ML decision or results. This would make it hard for the human operator to figure out how the AI algorithm arrived at the output. In some situations, such as in an augmented intelligence setup where the machine makes suggestions to the operator, this can be a problem if the operator is to determine how the suggestion arises in interpretation of the results. For example, it could be necessary to find out whether there is a false alarm or not.

It has been argued that the advantage of human involvement in the decision-making process is the ability to make accurate predictions from small amounts of training data. Human-in-the-loop is a proposed scheme to overcome the limitation of AI. Thus, the human could also guide the AI-enabled machine tool in the process [139]. An explainable interface could present a view of the algorithm, as well as the explanation of parameters as they flow through the algorithm. This would aim to help "decode" the processing to the user. Back to the example of false alarm, this would then enable the operator to decide whether to override the suggestion or not.

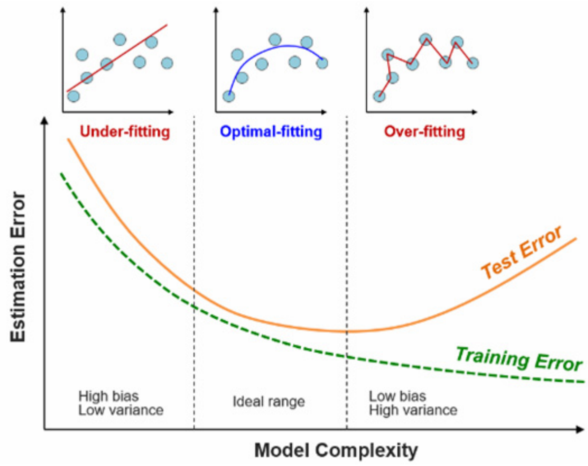


Fig. 11. Model complexity and estimation error.

However, the aim to implement explainable AI could also affect the choice of AI model to use in the self-optimizing system. For example, AI based on statistical methods would be more difficult to implement explainability relating to physics. Furthermore, depending on the choice of algorithm, certain limitations have greater effects on the explainability.

One example is the overfitting of data [140]. The concept is related to variance and bias. As one generalized example indicated in Fig. 11, a trend line that is very highly fit with the data would have very low training error but would lose sight of the pattern to be identified and produce high error when testing with another dataset. This negatively impacts the explainability of the machine learning output. Therefore, a balance between training error and testing error should be maintained as illustrated in Fig. 11. This consideration applies to other problems as well, for example classification.

One way to reduce overfitting is by using ensemble learning techniques such as bootstrap aggregating. The ensemble combines multiple hypotheses in the training process to improve prediction. Bootstrap aggregating involves having each trained model vote with equal weight. One example is combining random decision trees to achieve high classification accuracy. Multiple samples which are different from each other are generated in bootstrap aggregating and sent to multiple learners. Voting combines the result from each learner, therefore increasing prediction accuracy. As computing power continues to increase, this technique becomes more feasible.

An AI construction that employs a combination of methods could overcome the limitation of single choices. Although the biological neural network is still not well understood, cognitive science argues that the natural intelligent system is a hybrid that uses symbolic and subsymbolic operations. This inspires the construction of AI as a hybrid intelligence system to enable broader integration. This would make one component of AI interoperable with knowledgebases as the other component, thus increasing the explainability. One example is the fuzzy logic expert system which is based on a set of rules from experts.

4.4 Future outlooks

The ideal level of smart machining and machine tools should be supported by not only the data science for AI modeling, but also overall industrial advanced technologies such as low-cost pervasive sensors, high-speed communications, supercomputing, hyperconnected cloud service, and extended reality.

The first aspect is a fail-safe system through the redundant use of advanced sensors. The existing high-performance sensors are very expensive, so their use in the manufacturing site is limited. In addition, the sensors are sensitive to harsh machining environments, so they sometimes supply unreliable data and cause false alarms, which is critical in industrial sites where downtime is directly related to economic losses. On the other hand, low-cost micro-electromechanical systems (MEMS) and in-situ industrial internet of things (IIoT) sensors continue to advance in recent years. If multi-sensors can be redundantly installed in machine tools at low cost, it will be possible not only to supply a large amount of machining-related sensor data, but also to build a fail-safe system for smart machining through mutual complementation between different sensor signals to increase frequency bandwidths and accuracy as well as minimize imprecise data.

Another possibility for AI is the real-time processing of large volumes of data. The data communication speed is increasing with introduction to 5G and 6G in the near future. High-speed communications will have the capacity to increase the amount of data transmitted from machine tools to sensors, sensors to computers, computers to clouds, and clouds to machine tools again. This will move away from the current level of intermittent monitoring and anomaly detection for some targets and allow analyzing of all the machine parts and machining processes in real-time. In addition, real-time generated big data will be stored and AI processed through a so-called hyperconnected cloud platform.

The explosive improvement of AI performance is achieved through cloud and parallel processing. Currently, it is forecasted that a different level of computational speed will be possible through technologies such as ternary semiconductor and quantum computing. Until now, studies on AI modeling have put a lot of effort into efficient and automated feature extraction for high-dimensional data to avoid excessive computation. However, if such worries are resolved through supercomputing, multiple AI methods can be simultaneously processed by considering many more variables than what is currently possible. Additionally, it will be possible to make comprehensive decisions in real time by linking with the supply of vast amounts of data based on advanced low-cost sensors and high-speed communication mentioned above and to perform automated optimal machining control by feeding it back to the machine tool [141].

With the advanced technologies described above, AI will be able to make very accurate and rapid decisions; but for decisions related to overall productivity, humans must make a final decision that aggregates all external factors. Also, humans must learn to trust AI properly by watching its decision-making process [142]. In this context, extended reality (XR) such as augmented reality (AR) and virtual reality (VR), which have recently attracted great attention in various fields, will provide the interactive interface that intuitively shows the reasoning process and results of explainable AI. Especially in the case of smart machining, it can be imagined that practitioners remotely watch the real-time machining process that AI is working on through the XR interface, and sometimes answer the AI's questions if there is a significant issue to report.

5. Conclusions

Many machine tool companies and job shops are faced with fierce global competition to deliver products with improved productivity, flexibility, cost-effectiveness, and accuracy. AI has been employed by various industries, and the machine tool industry is showing great interest in adopting the new opportunity. The continuing development of sensing technologies combined with the industrial internet of things (IIoT) may help shape the trend. We examined different aspects of AI usage in machining operations such as thermal compensations, parameter optimization, chatter stability, tool wear and breakage monitoring, energy usage, etc. Many AI approaches available have been used to develop machining functions that involve problems such as classification, prediction, clustering, etc. in standalone situations with low error. This is achieved by using reliable data supplied from sources such as empirical or physical models. Sensor signals can be combined with AI approaches to identify conditions. When AI models correlate the effects between process parameters, they enable increased insight for the operator and adjustment of the process to reach the desired outcome. This offers faster feedback turnaround and possibility of further integration in cyber-physical machine tools.

Numerous interviews have found that domain experts who understand AI are needed to capitalize on AI-enabled smart machining. Particularly, machine tools and machining processes are quite complex. Many companies are collecting a lot of data without really knowing the exact usage of these data. The benefits of smart manufacturing come with associated challenges and risks. The critical questions we must ask are centered around data quality and security, transferability between different machines, workpieces, tools, etc. and ability to explain outputs. In order to address these challenges, the combination of traditional physical models, digital twin, machine learning, rule based expert approach, and human intelligence is needed to develop robust manufacturing processes.

Acknowledgements

This research was supported by the MSIT (Ministry of Science, ICT), Korea, under the High-Potential Individuals Global Training Program (2020-0-01529) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation), and by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2018R1A2A1A05079477).

References

[1] R. Geissbauer, S. Schrauf, P. Berttram and F. Cheraghi, *Digital Factories 2020 Shaping the Future of Manufacturing*, Pricewaterhouse Coopers, Germany (2017).
[2] M. Wetmore, *Industry 4.0: an Opportunity to Shine for Canadian Manufacturers*, Pricewaterhouse Coopers, Canada (2016).
[3] A. Iqbal, G. Zhao, H. Suhaimi, N. He, G. Hussain and W. Zhao, Readiness of subtractive and additive manufacturing and their sustainable amalgamation from the perspective of Industry 4.0: a comprehensive review, *The International Journal of Advanced Manufacturing Technology*, 111 (2020) 2475-2498.
[4] S. Jr. Kline, *2020 Capital Spending Machine Tools Survey*, Gardner Intelligence, USA (2020).
[5] H. Hassani, E. S. Silva, S. Unger, M. Tajmazinani and S. MacFeely, Artificial intelligence (AI) or intelligence augmentation (IA): what is the future, *AI*, 1 (2) (2020) 143-155.
[6] J. Johnson, *4 Types of AI*, BMC, Houston, Texas, USA (2020).
[7] M. I. Jordan and T. M. Mitchell, Review-machine learning: trends, perspectives, and prospects, *Science (Special Section: Artificial Intelligence)*, 349 (6245) (2015) 255-260.
[8] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali and R. Harik, A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces, and intelligence, *Journal of Manufacturing Systems*, 58 (B) (2021) 210-230.
[9] M. Matulis and C. Harvey, A robot arm digital twin utilizing reinforcement learning, *Computers and Graphics*, 95 (2021) 106-114.
[10] G. E. Hinton, S. Osindero and Y. Teh, A fast learning algorithm for deep belief nets, *Neural Computation*, 18 (7) (2006) 1527-1554.
[11] D. H. Kim, T. J. Y. Kim, X. Wang, M. Kim, Y. J. Quan, J. W. Oh, S. H. Min, H. Kim, B. Bhandari, I. Yang and S. H. Ahn, Smart machining process using machine learning: A review and perspective on machining industry, *International Journal of Precision Engineering and Manufacturing-Green Technology*, 5 (2018) 555-568.
[12] C. W. Chang, H. W. Lee and C. H. Liu, A review of artificial intelligence algorithms used for smart machine tools, *Inventions*, 3 (3) (2018) 41.
[13] T. Wuest, D. Weimer, C. Irgens and K. D. Thoben, Machine learning in manufacturing: advantages, challenges, and applications, *Production & Manufacturing Research*, 4 (1) (2016) 23-45.
[14] G. Seif, *The 5 Clustering Algorithms Data Scientists Need to Know*, Towards Data Science, Canada (2018).
[15] L. Maaten and G. Hinton, Visualizing data using t-SNE, *Journal of Machine Learning Research*, 9 (2008) 2579-2605.
[16] Y. Altintas, *Manufacturing Automation*, 2nd Ed., Cambridge University Press, New York, USA (2012).
[17] H. Cherukuri, E. Perez-Bernabeu, M. Selles and T. Schmitz, Machining chatter prediction using a data learning model, *Journal of Manufacturing Materials Processing*, 3 (2) (2019) 45-59.
[18] J. Karandikar, A. Honeycutt, T. Schmitz and S. Smith, Stability boundary and optimal operating parameter identification in milling using Bayesian learning, *Journal of Manufacturing Processes*, 56 (B) (2020) 1252-1262.
[19] Y. Fu, Y. Zhang, H. Qiao, D. Li, H. Zhou and J. Leopold, Analysis of feature extracting ability for cutting state monitoring using deep belief networks, *Procedia CIRP*, 31 (2015) 29-34.
[20] M. Lamraoui, M. Barak, M. Thomas and M. El Badoui, Chatter detection in milling machines by neural network classification and feature selection, *Journal of Vibration and Control*, 21 (7) (2015) 1251-1266.
[21] Z. Yao, D. Mei and Z. Chen, On-line chatter detection and identification based on wavelet and support vector machine, *Journal of Materials Processing Technology*, 210 (5) (2010) 713-719.
[22] M. Tran, M. Liu and Q. Tran, Milling chatter detection using scalogram and deep convolutional neural network, *The International Journal of Advanced Manufacturing Technology*, 107 (2020) 1505-1516.
[23] D. Zhang, G. Bi, Z. Sun and Y. Guo, Online monitoring of precision optics grinding using acoustic emission based on support vector machine, *International Journal of Advanced Manufacturing Technology*, 80 (2015) 761-774.
[24] Y. Dun, L. Zhu, B. Yan and S. Wang, A chatter detection method in milling of thin-walled TC4 alloy workpiece based on auto-encoding and hybrid clustering, *Mechanical Systems and Signal Processing*, 158 (2021) 107755.
[25] M. C. Yesilli, F. A. Khasawneh and A. Otto, On transfer learning for chatter detection in turning using wavelet packet transform and ensemble empirical mode decomposition, *CIRP Journal of Manufacturing Science and Technology*, 28 (2020) 118-135.
[26] L. T. Tunc, Smart tool path generation for 5-axis ball-end milling of sculptured surfaces using process models, *Robotics and Computer-Integrated Manufacturing*, 56 (2019) 212-221.
[27] L. T. Tunc and M. Zatarain, Stability optimal selection of stock shape and tool axis in finishing of thin-wall parts, *CIRP Annals*, 68 (1) (2019) 401-404.
[28] S. Chao and Y. Altintas, Chatter free tool orientations in 5-axis ball-end milling, *International Journal of Machine Tools and Manufacture*, 106 (2016) 89-97.
[29] Y. Yuan, H. T. Zhang, Y. Wu, T. Zhu and H. Ding, Bayesian learning-based model-predictive vibration control for thin-walled workpiece machining processes, *IEEE/ASME Transac-*

tions on Mechatronics, 22 (1) (2017) 509-520.

[30] Q. Guo, J. Yang and H. Wu, Application of ACO-BPN to thermal error modeling of NC machine tool, *The International Journal of Advanced Manufacturing Technology*, 50 (5-8) (2010) 667-675.

[31] J. Mayr, J. Jedrzejewski, E. Uhlmann, M. Alkan Donmez, W. Knapp, F. Härtig, K. Wendt, T. Moriwaki, P. Shore, R. Schmitt, C. Brecher, T. Würz and K. Wegener, Thermal issues in machine tools, *CIRP Annals - Manufacturing Technology*, 61 (2) (2012) 771-791.

[32] J. Vyroubal, Compensation of machine tool thermal deformation in spindle axis direction based on decomposition method, *Precision Engineering*, 36 (1) (2012) 121-127.

[33] B. Li, X. Tian and M. Zhang, Thermal error modeling of machine tool spindle based on the improved algorithm optimized BP neural network, *The International Journal of Advanced Manufacturing Technology*, 105 (1) (2019) 1497-1505.

[34] H. Wang, L. Wang, T. Li and J. Han, Thermal sensor selection for the thermal error modeling of machine tool based on the fuzzy clustering method, *The International Journal of Advanced Manufacturing Technology*, 69 (1-4) (2013) 121-126.

[35] M. Fujishima, K. Narimatsu, N. Irino, M. Mori and S. Ibaraki, Adaptive thermal displacement compensation method based on deep learning, *CIRP Journal of Manufacturing Science and Technology*, 25 (2019) 22-25.

[36] C. H. Lo, J. Yuan and J. Ni, Optimal temperature variable selection by grouping approach for thermal error modeling and compensation, *International Journal of Machine Tools and Manufacture*, 39 (9) (1999) 1383-1396.

[37] S. Yang, J. Yuan and J. Ni, The improvement of thermal error modeling and compensation on machine tools by CMAC neural network, *International Journal of Machine Tools and Manufacture*, 36 (4) (1996) 527-537.

[38] C. Ma, L. Zhao, X. Mei, H. Shi and J. Yang, Thermal error compensation based on genetic algorithm and artificial neural network of the shaft in the high-speed spindle system, *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 231 (5) (2017) 753-767.

[39] C. Ma, L. Zhao, X. Mei, H. Shi and J. Yang, Thermal error compensation of high-speed spindle system based on a modified BP neural network, *The International Journal of Advanced Manufacturing Technology*, 89 (9-12) (2017) 3071-3085.

[40] Y. Zhang, J. Yang and H. Jiang, Machine tool thermal error modeling and prediction by grey neural network, *The International Journal of Advanced Manufacturing Technology*, 59 (9-12) (2012) 1065-1072.

[41] A. M. Abdulshahed, A. P. Longstaff, S. Fletcher and A. Potdar, Thermal error modelling of a gantry-type 5-axis machine tool using a grey neural network model, *Journal of Manufacturing Systems*, 41 (2016) 130-142.

[42] K. C. Wang, P. C. Tseng and K. M. Lin, Thermal error modeling of a machining center using grey system theory and adaptive network-based fuzzy inference system, *International Journal Series C Mechanical Systems, Machine Elements and Manufacturing*, 49 (4) (2006) 1179-1187.

[43] A. M. Abdulshahed, A. P. Longstaff and S. Fletcher, A cuckoo search optimisation-based Grey prediction model for thermal error compensation on CNC machine tools, *Grey Systems: Theory and Application*, 7 (2) (2017) 146-155.

[44] P. Liu, Z. Du, H. Li, M. Deng, X. Feng and J. Yang, Thermal error modeling based on BiLSTM deep learning for CNC machine tool, *Advanced Manufacturing*, 9 (2021) 235-249.

[45] W. Chengyang, X. Sitong and X. Wansheng, Spindle thermal error prediction approach based on thermal infrared images: a deep learning method, *Journal of Manufacturing Systems*, 59 (2021) 67-80.

[46] K. Liu, L. Song, W. Han, Y. Cui and Y. Wang, Time-varying error prediction and compensation for movement axis of CNC machine tool based on digital twin, *IEEE Transactions on Industrial Informatics*, 18 (1) (2022) 109-117.

[47] J. Liu, H. Gui and C. Ma, Digital twin system of thermal error control for a large-size gear profile grinder enabled by gated recurrent unit, *Journal of Ambient Intelligence and Humanized Computing* (2021).

[48] Y. F. Li, X. X. Han and S. Y. Li, Non-contact dimension measurement of mechanical parts based on image processing, *8th International Congress on Image and Signal Processing (CISP)*, Shenyang, PRC (2015) 974-978.

[49] K. Khalili and M. Vahidnia, Improving the accuracy of crack length measurement using machine vision, *Procedia Technology*, 19 (2015) 48-55.

[50] Z. Wei, B. Zhang and P. Liu, Object dimension measurement based on mask R-CNN, *12th International Conference on Intelligent Robotics and Applications*, Shenyang, PRC (4) (2019) 320-330.

[51] S. P. Lo, An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling, *Journal of Materials Processing Technology*, 142 (2003) 665-675.

[52] W. H. Ho, J. T. Tsai, B. T. Lin and J. H. Chou, Adaptive network-based fuzzy inference system for prediction of surface roughness in end milling process using hybrid Taguchi-genetic learning algorithm, *Expert Systems with Applications*, 36 (2) (2009) 3216-3222.

[53] Z. Jurkovic, G. Cukor, M. Brezocnik and T. Brajkovic, A comparison of machine learning methods for cutting parameters prediction in high speed turning process, *Journal of Intelligent Manufacturing*, 29 (2018) 1683-1693.

[54] I. Svalina, G. Simunovic, T. Saric and R. Lujic, Evolutionary neuro-fuzzy system for surface roughness evaluation, *Applied Soft Computing*, 52 (2017) 593-604.

[55] L. C. Moreira, L. D. Li, X. Lu and M. E. Fitzpatrick, Supervision controller for real-time surface quality assurance in CNC machining using artificial intelligence, *Computers & Industrial Engineering*, 127 (2019) 158-168.

[56] R. H. Guerra, R. Quiza, A. Villalonga, J. Arenas and F. Castano, Digital twin-based optimization for ultraprecision motion systems with backlash and friction, *IEEE Access*, 7 (2019) 93462-93472.

[57] G. Kant and K. S. Sangwan, Predictive modelling and optimization of machining parameters to minimize surface roughness

using artificial neural network coupled with genetic algorithm, *Procedia CIRP*, 31 (2015) 453-458.

[58] S. Wang, X. Lu, X. X. Li and W. D. Li, A systematic approach of process planning and scheduling optimization for sustainable machining, *Journal of Cleaner Production*, 87 (2015) 914-929.

[59] J. Lipski and K. Zaleski, Implementation of artificial intelligence in optimization of technological processes, *MATEC Web of Conferences*, 252 (2019) 03008.

[60] D. Karayel, Prediction and control of surface roughness in CNC lathe using artificial neural network, *Journal of Materials Processing Technology*, 209 (7) (2009) 3125-3137.

[61] U. Zuperl, F. Cus and M. Reibenschuh, Modeling and adaptive force control of milling by using artificial techniques, *Journal of Intelligent Manufacturing*, 23 (5) (2012) 1805-1815.

[62] U. Zuperl and F. Cus, Surface roughness fuzzy inference system within the control simulation of end milling, *Precision Engineering*, 43 (2016) 530-543.

[63] E. Ülker, M. E. Turanalp and H. S. Halkaci, An artificial immune system approach to CNC tool path generation, *Journal of Intelligent Manufacturing*, 20 (1) (2009) 67-77.

[64] H. El-Mounayri and H. Deng, A generic and innovative approach for integrated simulation and optimisation of end milling using solid modelling and neural network, *International Journal of Computer Integrated Manufacturing*, 23 (1) (2010) 40-60.

[65] J. Balic and M. Korosec, Intelligent tool path generation for milling of free surfaces using neural networks, *International Journal of Machine Tools and Manufacture*, 42 (10) (2002) 1171-1179.

[66] H. Ghaiebi and M. Solimanpur, An ant algorithm for optimization of hole-making operations, *Computers & Industrial Engineering*, 52 (2) (2007) 308-319.

[67] A. T. Abbas, M. F. Aly and K. Hamza, Optimum drilling path planning for a rectangular matrix of holes using ant colony optimization, *International Journal of Production Research*, 49 (19) (2011) 5877-5891.

[68] B. Li, H. Zhang, P. Ye and J. Wang, Trajectory smoothing method using reinforcement learning for computer numerical control machine tools, *Robotics and Computer-Integrated Manufacturing*, 61 (2020) 101847.

[69] B. Denkena, E. Abele, C. Brecher, M. A. Dittrich, S. Kara and M. Mori, Energy efficient machine tools, *CIRP Annals-Manufacturing Technology*, 69 (2020) 646-667.

[70] Okuma America Corporation, *Energy-Efficient Machine Tool Technologies, For Any Size Shop [White paper]*, Charlotte, North Carolina, USA (2015).

[71] A. Vijayaraghavan and D. Dornfeld, Automated energy monitoring of machine tools, *CIRP Annals*, 59 (1) (2010) 21-24.

[72] G. Y. Zhao, Z. Y. Liu, Y. He, H. J. Cao and Y. B. Guo, Energy consumption in machining: classification, prediction, and reduction strategy, *Energy*, 133 (2017) 142-157.

[73] N. Sihag and K. S. Sangwan, A systematic literature review on machine tool energy consumption, *Journal of Cleaner Production*, 275 (2020) 123125.

[74] G. Kant and K. S. Sangwan, Predictive modelling for energy consumption in machining using artificial neural network, *Procedia CIRP*, 37 (2015) 205-210.

[75] G. Zhao, Q. Zhao, G. Zheng and J. Zhai, Specific energy consumption prediction method based on machine tool power measurement, *Sensors & Transducers*, 174 (2014) 115-122.

[76] X. Zhang, Q. Zhu, Y. He and Y. Xu, Energy modeling using an effective latent variable based functional link learning machine, *Energy*, 162 (2018) 883-891.

[77] Z. Liu, X. Wang, Q. Zhang and C. Huang, Empirical mode decomposition based hybrid ensemble model for electrical energy consumption forecasting of the cement grinding process, *Measurement*, 138 (2019) 314-324.

[78] R. Ak, M. M. Helu and S. Rachuri, Ensemble neural network model for predicting the energy consumption of a milling machine, *Proceedings of the ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Boston, Massachusetts, USA (2015) 1-7.

[79] Q. Xiao, C. Li, Y. Tang, Y. Du and Y. Kou, Deep learning based modeling for cutting energy consumed in CNC turning process, *Proceedings of IEEE International Conference on Systems, Man, and Cybernetics*, Miyazaki, Japan (2018) 1398-1403.

[80] Z. W. Zhang, R. Z. Tang, T. Peng, L. Y. Tao and S. Jia, A method for minimizing the energy consumption of machining system: integration of process planning and scheduling, *Journal of Cleaner Production*, 137 (2016) 1647-1662.

[81] D. Flum, J. Sossenheimer, C. Stück and E. Abele, Towards energy-efficient machine tools through the development of the twin-control energy efficiency module, M. Armendia, M. Ghassempouri, E. Ozturk, and F. Peysson (Eds.), *Twin-Control*, Springer, Cham, Switzerland (2019) 95-108.

[82] The British Standards Institution, *BS EN 13306, Maintenance - Maintenance Terminology*, London, UK (2010).

[83] M. Rausand and A. Hoyland, *System Reliability Theory: Models, Statistical Methods, and Applications,* John Wiley & Sons, Hoboken, New Jersey, USA, 396 (2003).

[84] C. Okoh, R. Roy and J. Mehnen, Predictive maintenance modelling for through-life engineering services, *Procedia CIRP*, 59 (2017) 196-201.

[85] G. W. Vogl, B. A. Weiss and M. Helu, A review of diagnostic and prognostic capabilities and best practices for manufacturing, *Journal of Intelligent Manufacturing*, 30 (1) (2019) 79-95.

[86] C. Ly, K. Tom, C. S. Byington, R. Patrick and G. J. Vachtsevanos, Fault diagnosis and failure prognosis for engineering systems: a global perspective, *2009 IEEE International Conference on Automation Science and Engineering*, Bengalore, India (2009) 108-115.

[87] International Standards Organization, *ISO 13381-1, Condition Monitoring and Diagnostics of Machines - Prognostics - Part 1: General Guidelines*, Geneva, Switzerland (2004).

[88] H. M. Elattar, H. K. Elminir and A. M. Riad, Prognostics: a literature review, *Complex & Intelligent Systems*, 2 (2) (2016) 125-154.

[89] L. Liao and F. Köttig, Review of hybrid prognostics ap-

proaches for remaining useful life prediction of engineered systems, and an application to battery life prediction, *IEEE Transactions on Reliability*, 63 (1) (2014) 191-207.
[90] H. Hanachi, W. Yu, I. Y. Kim, J. Liu and C. K. Mechefske, Hybrid data-driven physics-based model fusion framework for tool wear prediction, *The International Journal of Advanced Manufacturing Technology*, 101 (9) (2019) 2861-2872.
[91] J. Caldeirani Filho and A. E. Diniz, Influence of cutting conditions on tool life, tool wear and surface finish in the face milling process, *Journal of the Brazilian Society of Mechanical Sciences*, 24 (2002) 10-14.
[92] X. Cui, J. Zhao and Y. Dong, The effects of cutting parameters on tool life and wear mechanisms of CBN tool in high-speed face milling of hardened steel, *The International Journal of Advanced Manufacturing Technology*, 66 (5) (2013) 955-964.
[93] D. A. Stephenson and J. S. Agapiou, *Metal Cutting Theory and Practice*, CRC Press, Boca Ranton, Florida, USA (2006).
[94] Y. Zhou and W. Xue, Review of tool condition monitoring methods in milling processes, *The International Journal of Advanced Manufacturing Technology*, 96 (5) (2018) 2509-2523.
[95] G. Serin, B. Sener, A. M. Ozbayoglu and H. O. Unver, Review of tool condition monitoring in machining and opportunities for deep learning, *The International Journal of Advanced Manufacturing Technology*, 109 (3) (2020) 953-974.
[96] Y. Zhang, K. Zhu, X. Duan and S. Li, Tool wear estimation and life prognostics in milling: Model extension and generalization, *Mechanical Systems and Signal Processing*, 155 (2021) 107617.
[97] G. Xu, M. Liu, J. Wang, Y. Ma, J. Wang, F. Li and W. Shen, Data-driven fault diagnostics and prognostics for predictive maintenance: a brief overview, *IEEE 15th International Conference on Automation Science and Engineering (CASE)*, Vancouver, BC, Canada (2019) 103-108.
[98] Y. Lei, N. Li, L. Guo, N. Li, T. Yan and J. Lin, Machinery health prognostics: a systematic review from data acquisition to RUL prediction, *Mechanical Systems and Signal Processing*, 104 (2018) 799-834.
[99] M. Liu, X. Yao, J. Zhang, W. Chen, X. Jing and K. Wang, Multi-sensor data fusion for remaining useful life prediction of machining tools by IABC-BPNN in dry milling operations, *Sensors*, 20 (17) (2020) 4657.
[100] W. H. Hsieh, M. C. Lu and S. J. Chiou, Application of backpropagation neural network for spindle vibration-based tool wear monitoring in micro-milling, *The International Journal of Advanced Manufacturing Technology*, 61 (2012) 53-61.
[101] S. Shankar, T. Mohanraj and R. Rajasekar, Prediction of cutting tool wear during milling process using artificial intelligence techniques, *International Journal of Computer Integrated Manufacturing*, 32 (2) (2019) 174-182.
[102] Y. Zhou, B. Sun, W. Sun and Z. Lei, Tool wear condition monitoring based on a two-layer angle kernel extreme learning machine using sound sensor for milling process, *Journal of Intelligent Manufacturing* (2020).
[103] R. Teti, K. Jemielniak, G. O'donnell and D. Dornfeld, Advanced monitoring of machining operations, *CIRP Annals*, 59 (2) (2010) 717-739.
[104] M. Kuntoğlu, A. Aslan, D. Y. Pimenov, U. A. Usca, E. Salur, M. K. Gupta, T. Mikolajczyk, K. Giasin, W. Kaplonek and S. Sharma, A review of indirect tool condition monitoring systems and decision-making methods in turning: critical analysis and trends, *Sensors*, 21 (1) (2021) 108.
[105] B. Cuka and D. W. Kim, Fuzzy logic based tool condition monitoring for end-milling, *Robotics and Computer-Integrated Manufacturing*, 47 (2017) 22-36.
[106] T. Mohanraj, S. Shankar, R. Rajasekar, N. R. Sakthivel and A. Pramanik, Tool condition monitoring techniques in milling process — a review, *Journal of Materials Research and Technology*, 9 (1) (2020) 1032-1042.
[107] K. Zhu, Y. S. Wong and G. S. Hong, Wavelet analysis of sensor signals for tool condition monitoring: a review and some new results, *International Journal of Machine Tools and Manufacture*, 49 (7) (2009) 537-553.
[108] D. D'Addona, T. Segreto, A. Simeone and R. Teti, ANN tool wear modelling in the machining of nickel superalloy industrial products, *CIRP Journal of Manufacturing Science and Technology*, 4 (1) (2011) 33-37.
[109] R. H. L. da Silva, M. B. da Silva and A. Hassui, A probabilistic neural network applied in monitoring tool wear in the end milling operation via acoustic emission and cutting power signals, *Machining Science and Technology*, 20 (3) (2016) 386-405.
[110] A. Gouarir, G. Martinez-Arellano, G. Terrazas, P. Bernados and S. Ratchev, In-process tool wear prediction system based on machine learning techniques and force analysis, *Procedia CIRP*, 77 (2018) 501-504.
[111] W. Cai, W. Zhang, X. Hu and Y. Liu, A hybrid information model based on long short-term memory network for tool condition monitoring, *Journal of Intelligent Manufacturing*, 31 (2020) 1497-1510.
[112] C. Zhang, X. Yao, J. Zhang and H. Jin, Tool condition monitoring and remaining useful life prognostic based on a wireless sensor in dry milling operations, *Sensors*, 16 (6) (2016) 795.
[113] L. Xu, C. Huang, C. Li, J. Wang, H. Liu and X. Wang, Estimation of tool wear and optimization of cutting parameters based on novel ANFIS-PSO method toward intelligent machining, *Journal of Intelligent Manufacturing*, 32 (2021) 77-90.
[114] A. J. Torabi, M. J. Er, X. Li, B. S. Lim and G. O. Peen, Application of clustering methods for online tool condition monitoring and fault diagnosis in high-speed milling processes, *IEEE Systems Journal*, 10 (2) (2016) 721-732.
[115] P. Stavropoulos, A. Papacharalampopoulos, E. Vasiliadis and G. Chryssolouris, Tool wear predictability estimation in milling based on multi-sensorial data, *The International Journal of Advanced Manufacturing Technology*, 82 (2016) 509-521.
[116] Q. Ren, L. Baron, M. Balazinski, R. Botez and P. Bigras, Tool wear assessment based on type-2 fuzzy uncertainty estimation on acoustic emission, *Applied Soft Computing*, 31 (2015) 14-24.
[117] V. Pandiyan, W. Caeserendra, T. Tjahjowidodo and H. H.

Tan, In-process tool condition monitoring in compliant abrasive belt grinding process using support vector machine and genetic algorithm, *Journal of Manufacturing Processes*, 31 (2018) 199-213.

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

[119] T. Benkedjouh, K. Medjaher, N. Zerhouni and S. Rechak, Health assessment and life prediction of cutting tools based on support vector regression, *Journal of Intelligent Manufacturing*, 26 (2) (2015) 213-223.

[120] W. Li and T. Liu, Time varying and condition adaptive hidden Markov model for tool wear state estimation and remaining useful life prediction in micro-milling, *Mechanical Systems and Signal Processing*, 131 (2019) 689-702.

[121] M. Elangovan, K. I. Ramachandran and V. Sugumaran, Studies on Bayes classifier for condition monitoring of single point carbide tipped tool based on statistical and histogram features, *Expert Systems with Applications*, 37 (3) (2010) 2059-2065.

[122] S. Laddada, M. O. Si-Chaib, T. Benkedjouh and R. Drai, Tool wear condition monitoring based on wavelet transform and improved extreme learning machine, *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 234 (5) (2019) 1057-1068.

[123] W. Luo, T. Hu, Y. Ye, C. Zhang and Y. Wei, A hybrid predictive maintenance approach for CNC machine tool driven by digital twin, *Robotics and Computer Integrated Manufacturing*, 65 (2020) 101974.

[124] H. Saglam, Tool wear monitoring in bandsawing using neural networks and Taguchi's design of experiments, *The International Journal of Advanced Manufacturing Technology*, 55 (2011) 969-982.

[125] D. Shi and N. Gindy, Tool wear predictive model based on least squares support vector machines, *Mechanical Systems and Signal Processing*, 21 (4) (2007) 1799-1814.

[126] W. Caesarendra, T. Triwiyanto, V. Pandiyan, A. Glowacz, S. D. H. Permana and T. Tjahjowidodo, A CNN prediction method for belt grinding tool wear in a polishing process utilizing 3-axes force and vibration data, *Electronics*, 10 (12) (2021) 1429.

[127] H. Oo, W. Wang and Z. Liu, Tool wear monitoring system in belt grinding based on image-processing techniques, *The International Journal of Advanced Manufacturing Technology*, 111 (2020) 2215-2229.

[128] A. Kumar, R. B. Chinnam and F. Tseng, An HMM and polynomial regression based approach for remaining useful life and health state estimation of cutting tools, *Computers & Industrial Engineering*, 128 (2019) 1008-1014.

[129] J. Dou, C. Xu, S. Jiao, B. Li, J. Zhang and X. Xu, An unsupervised online monitoring method for tool wear using a sparse auto-encoder, *The International Journal of Advanced Manufacturing Technology*, 106 (5) (2020) 2493-2507.

[130] I. Goodfellow, Y. Bengio and A. Courville, *Deep Learning*, MIT Press, Cambridge, Massachusetts, USA (2016).

[131] G. Press, Cleaning big data: most time-consuming, least enjoyable data science task, survey says, *Forbes* (2016).

[132] C. Lin, T. Chen, L. Wang and H. Shuai, Health-based fault generative adversarial network for fault diagnosis in machine tools, *Artificial Intelligence of Things Workshop in Association for the Advancement of Artificial Intelligence Conference*, New York, USA (2020).

[133] G. Chhabra, V. Vashisht and J. Ranjan, A review on missing data value estimation using imputation algorithm, *Journal of Advanced Research in Dynamical and Control Systems*, 11 (7) (2019) 312-318.

[134] S. Han, H. J. Choi, S. K. Choi and J. S. Oh, Fault diagnosis of planetary gear carrier packs: A class imbalance and multi-class classification problem, *International Journal of Precision Engineering and Manufacturing*, 20 (2019) 167-179.

[135] B. Roy, *All About Feature Scaling*, Towards Data Science, Canada (2020).

[136] S. Shao, S. McAleer, R. Yan and P. Baldi, Highly accurate machine fault diagnosis using deep transfer learning, *IEEE Transactions on Industrial Informatics*, 15 (4) (2019) 2446-2455.

[137] F. Yang, W. Zhang, L. Tao and J. Ma, Transfer learning strategies for deep learning-based PHM algorithms, *Applied Sciences*, 10 (7) (2020) 2361.

[138] P. Cao, S. Zhang and J. Tang, Preprocessing-free gear fault diagnosis using small datasets with deep convolutional neural network-based transfer learning, *IEEE Access*, 6 (2018) 26241-26253.

[139] R. Sawhney, *Human in the Loop: Why We Will be Needed to Complement Artificial Intelligence*, The London School of Economics and Political Science Business Review, London, UK (2018).

[140] A. Widodo and B. S. Yang, Support vector machine in machine condition monitoring and fault diagnosis, *Mechanical Systems and Signal Processing*, 21 (6) (2007) 2560-2574.

[141] J. Chen, P. Hu, H. Zhou, J. Yang, J. Xie, Y. Jiang, Z. Gao and C. Zhang, Toward intelligent machine tool, *Engineering*, 5 (4) (2019) 679-690.

[142] Z. H. Zhou, Machine learning challenges and impact: an interview with Thomas Dietterich, *National Science Review*, 5 (1) (2018) 54-58.

Simon S. Park is a Professor at the Schulich School of Engineering, Dept. of Mechanical and Manufacturing Engineering, University of Calgary, Canada. He was an AITF iCORE Chair in sensing and monitoring. He is a professional engineer in Alberta and is an associate member of CIRP (Int. Academy of Production Engineers) from Canada. Dr. Park received bachelor and master's degrees from the University of Toronto, Canada. He then continued his Ph.D. at the University of British Columbia, Canada.