REVIEW PAPER
DOI: 10.1007/s40684-018-0057-y
ISSN 2288-6206 (Print) / 2198-0810 (Online)

Smart Machining Process Using Machine Learning: A Review and Perspective on Machining Industry

Dong-Hyeon Kim[1,2], Thomas J. Y. Kim[1], Xinlin Wang[1], Mincheol Kim[1,3], Ying-Jun Quan[1], Jin Woo Oh[1], Soo-Hong Min[1], Hyungjung Kim[4], Binayak Bhandari[5], Insoon Yang[6], and Sung-Hoon Ahn[1,4,#]

1 Department of Mechanical and Aerospace Engineering, Seoul National University, Seoul, 08826, Republic of Korea
2 BK21 Plus Transformative Training Program for Creative Mechanical and Aerospace Engineers, Seoul National University, Seoul, 08826, Republic of Korea
3 Optical Instrumentation Research Center, Korea Basic Science Institute, Daejeon, 34133, Republic of Korea
4 Institute of Advanced Machines and Design (IAMD), Seoul National University, Seoul, 08826, Republic of Korea
5 Department of Railroad Integrated System, Woosong University, Daejeon, 34518, Republic of Korea
6 Department of Electrical and Computer Engineering, Automation and Systems Research Institute, Seoul National University, Seoul, 08826, Republic of Korea
Corresponding Author / E-mail: ahnsh@snu.ac.kr, TEL: +82-2-880-7110
ORCID: 0000-0002-1548-2394

KEYWORDS: 4th industrial revolution, Artificial intelligence, Machine learning, Machining process, Machining industry

The Fourth Industrial Revolution incorporates the digital revolution into the physical world, creating a new direction in a number of fields, including artificial intelligence, quantum computing, nanotechnology, biotechnology, robotics, 3D printing, autonomous vehicles, and the Internet of Things. The artificial intelligence field has encountered a turning point mainly due to advancements in machine learning, which allows machines to learn, improve, and perform a specific task through data without being explicitly programmed. Machine learning can be utilized with machining processes to improve product quality levels and productivity rates, to monitor the health of systems, and to optimize design and process parameters. This is known as smart machining, referring to a new machining paradigm in which machine tools are fully connected through a cyber-physical system. This paper reviews and summarizes machining processes using machine learning algorithms and suggests a perspective on the machining industry.

Manuscript received: March 1, 2018 / Revised: July 12, 2018 / Accepted: August 8, 2018 (Invited Paper)

1. Introduction

Following the Fourth Industrial Revolution, the global manufacturing sector is now working on smart factories to prepare for the decline in the value added in the manufacturing industries and to improve productivity. Many technologies, such as the Internet of Things (IoT), cyber-physical systems (CPS), big data, smart sensors, and 3D printing, have been developed to a level that makes them now applicable to the manufacturing field. Among these technologies, IoT and big data are most commonly used because smart factories manage entire systems based on information gathered from sensors attached to all machines in the factory.[1,2] Through IoT, the manufacturing ecosystem is established and synchronized with various information systems for production management purposes.[3] CPS is also an essential element focused on services and applications provided by the cyber world; it allows production-related data acquisition in the real world and supports smart production based on software, sensors, and information processing devices.[4-7]

Artificial intelligence refers to the ability of computers to exhibit characteristics that humans would perceive as being intelligent. Although the term artificial intelligence has long been used, research in this field has been flourishing due to recent advancements in information processing technology. Global companies such as Google, Facebook, Alibaba, IBM, FANUC and Samsung are constantly strengthening their artificial intelligence research. There has been a steady increase in the demand for creating value from the large amounts of data accumulated by various industries, such as information technology,[8] finance,[9] food production,[10] chemical industry,[11] health care,[10] and manufacturing.[11]

The field of artificial intelligence has reached a turning point mainly due to advancements in machine learning, which is a subfield of artificial intelligence that allows machines to learn, improve, and perform a specific task using data without being explicitly programmed. Many of the recent achievements in artificial intelligence are based on machine learning.

The problem solving process using machine learning can be generally represented through the steps shown in Fig. 1.[12] First, the

Fig. 1 Problem solving process using machine learning

problem must be defined and the appropriate machine learning analysis method must be selected. According to the defined problem and the analysis method, the necessary data must be collected and preprocessed into a form that can be directly used for the subsequent analysis. A model for the data is then developed and evaluated. Finally, the results are analyzed to obtain the solution for the problem. Several iterations are typically required in order to obtain the improved results.

Machine learning algorithms can be divided into three categories based on the learning system and the type of input data. The first is supervised learning, where the algorithms are trained to map given inputs to corresponding known outputs (provided by human experts). The second is unsupervised learning, which involves the process of developing a model or function without inputting the known outputs. This method is typically used for finding meaningful patterns or classifications within a large data set. Finally, there is reinforcement learning, the process of learning through a predefined reward signal that enables the machine to be able to quantify its performance. These algorithms attempt to do two main tasks: classification or clustering, in which the data is separated into specific classes, and regression, in which a continuous trend or relationship is sought. The different methods used to achieve these tasks will determine the type of algorithm used, such as support vector machines, artificial neural networks, decision trees, naïve Bayes, k-nearest neighbors, and so on.[13-18]

Smart machining is a machining process that is able to adjust its parameters autonomously during the machining process to achieve a certain objective. During conventional machining processes, the operation conditions are not always ideal due to the various errors present during the material removal process, such as geometric errors, thermal deformation, elastic deformation, and vibration. Smart machining can be developed through the establishment of interactions with different systems, including machine tools, sensors and controller networks, simulation-based designs, big data and cloud-based systems, as well as smart control algorithms. The smart machining process can be implemented in order to optimize process parameters automatically in real time, obtaining optimum processing performance and product quality. During the machining process, various factors affect the product quality, such as the workpiece properties, the machines used, the cutting tools, and the cutting conditions. In addition, the control parameters need to be optimized during the handling and positioning operations, as these operations account for more than 50% of the overall processing time.[19]

In this paper, machining processes using machine learning techniques and algorithms are reviewed and summarized. A perspective on the machining industry is also provided.

2. Machining Processes Using Machine Learning

Many researchers have studied the use of machine learning in various types of manufacturing industries.[5,20-29] This section focuses on different cases of smart machining processes using machine learning, as listed in Table 1. As the working principles of the different types of machine learning algorithms are readily available, only the implementation details to the machining processes are summarized.

2.1 Conventional Machining

Conventional machining processes are most commonly studied in relation to the use of machine-learning algorithms. The purposes vary, ranging from process parameter optimization to machine health monitoring and product quality enhancement. Milling and turning were the most prominent forms of conventional machining processes studied.

2.1.1 Milling

There have been many studies on the implementation of machine learning algorithms to milling processes, and a total of 14 cases are reviewed here. Through the use of machine learning algorithms, various factors or parameters were monitored and predicted, a task that would have been difficult to achieve through conventional methods. The most common purpose has been to monitor the tool condition, keeping track of its wear and its potential for failure. Since a classification algorithm is required for this purpose, algorithms such as support vector machine (SVM),[15,30-34] artificial neural network (ANN),[35-43] and decision trees, as well as its subtypes, such as probabilistic neural network (PNN),[13,44] backpropagation neural network algorithm (BpNN),[45,46] and random forest (RF),[8] were commonly used. However, other tasks were also achieved, such as process parameter optimization for cost reduction through energy consumption predictions, and product quality enhancements through predictions of surface roughness, cutting force, and workpiece deformation. For such purposes, a popular choice was also SVM, but other algorithms, such as Gaussian process regression (GPR),[47,48] Non-dominated sorting genetic algorithm II (NSGA-II),[49] and other statistical methods were also used.[36,50]

2.1.2 Turning

Machine learning has also been applied extensively to the turning process, achieving tasks that are similar to those of the previously mentioned milling process, specifically tool condition monitoring and surface roughness predictions. Although ANNs were mostly used for tool wear predictions, various kinds of regression algorithms, such as support vector regression (SVR)[10] and polynomial regression, were used for surface roughness predictions. Pontes et al.[45] reviewed in detail the use of ANNs for surface roughness predictions in machining processes. Additionally, other tasks, such as carbon emission, microhardness, and grain size predictions, were achieved. For instance, through a combination of RF and GA,[51,52] Arisoy et al.[8] studied the effects of the cutting speed, feed rate, tool edge radius, and tool coating on certain surface characteristics, specifically the machining-induced microhardness and grain size. Lin et al.[53] predicted carbon emissions produced during the turning process through regression and Multi-objective teaching learning based optimization (MOTLBO).

2.1.3 Grinding

Although not many cases for smart grinding processes were found, similar efforts to predict the finishing quality were observed. Zhang et

Table 1 Cases of machining processes using machine learning

Process	Purpose	Algorithms	Input parameters	Preprocessing	Accuracy*	Ref. (Year)
Milling	Tool wear monitoring	K-NN, SVM	Tool images	Shape and contour descriptors	90.26%	[55] (2017)
	Tool breakage detection	SVM, SVR	Cutting force and power consumption data	N/A	99.38%	[56] (2005)
	Tool wear prediction	RF	Cutting force, vibration, acoustic emission	Statistical features (max, median, mean, standard deviation)	99.20%	[57] (2017)
	Energy consumption prediction	Gaussian process regression	Spindle speed, feed rate, depth of cut, active tool axis, cutting strategy	N/A	Above 95%	[58] (2015)
	Tool wear and remaining useful life (RUL) prediction	SVR	Vibration, cutting force, acoustic emissions	Wavelet packet decomposition, expectation-maximization principal component analysis (PCA), isometric feature mapping	98.95% (for cutter 3)	[10] (2015)
	Energy consumption prediction	GPR (global and collective)	Spindle speed, feed rate, active tool cutting direction, depth of cut, cutting strategy, length of tool path	Gaussian mixture model	98.66% (global GPR), 98.07% (collective GPR)	[59] (2014)
	Tool breakage detection	PNN	Spindle speed, feed rate, depth of cut, max peak force, max variance pack force	N/A	98.60%	[44] (2015)
	Optimize tool path, tool selection, cutting parameters and evaluate proposed solution	NSGA-II	CAD model	N/A	N/A	[60] (2016)
	Surface roughness prediction	SVM (radial basis function kernel)	Spindle speed, depth of cut, feed speed	Normalization	86.50%	[30] (2016)
	Chatter stability lobes prediction	SVM (radial basis function kernel)	Vibration signal (cutting force in x and y direction)	Wavelet packet transform, wavelet energy entropy theory, normalization	98.33%	[31] (2015)
	Tool condition monitoring (good, midlife, worn-out)	J48 Decision Tree, Feed forward BpNN	Vibration signals (from accelerometer)	Fast Fourier transform, statistical features (mean, standard error and deviation, kurtosis, etc.)	94.30% (J48), 95.40% (NN)	[61] (2015)
	Determination of individual specific cutting forces	BpNN	Material, cutting material, coating, tool diameter, cutting speed, feed rate, depth of cut, entry/exit angle, average chip thickness, etc.	N/A	87.44%	[62] (2017)
	Prediction of deformations in thin-walled workpiece machining processes (milling), vibration control implementation	Bayesian learning method	Historical displacement information	N/A	N/A	[37] (2017)
Turning	Surface roughness prediction	Multiple linear regression (MLR)	Speed, feed, depth of cut, flank wear, vibration	Statistical features (mean, standard error, median, kurtosis, etc.), PCA	80.80%	[63] (2015)

Table 1 Continued

Process	Purpose	Algorithms	Input parameters	Preprocessing	Accuracy*	Ref. (Year)
Turning	Prediction of machining parameters (surface roughness, cutting force, tool lifetime)	SVR (linear, polynomial, radial basis function kernel), polynomial regression, ANNs	Cutting speed, depth of cut, feed rate	Regularization	92.48% (R_a with polynomial regression), 93.63% (cutting force with polynomial regression), 93.15% (tool life with ANNs)	64 (2016)
	Microhardness and grain size prediction	RF, GA	Cutting speed, feed rate, tool edge radius, tool coating status	N/A	96.50%	8 (2015)
	Carbon emission quantification and prediction, cutting parameter optimization	Regression, MOTLBO	Speed, feed, depth of cut	Response surface method, grey relational analysis(GRA)	Above 95%	53 (2015)
	Tool wear prediction and pattern recognition	Cascade forward BpNN, DNA-based computing	Machining time, cutting speed, feed rate, depth of cut, avg. number of white pixels from tool image	Image processing (Gaussian blur), binary image data	75%	65 (2017)
	Tool condition monitoring (4 conditions: good, less blunt, highly blunt, loose)	K-Star algorithm	Vibration signals	Statistical features (standard error and deviation, variance, kurtosis, etc.), correlation-based attribute subset selection	78.69%	66 (2014)
	Online Tool Life Prediction	Cascade-forward NN, Feed-forward NN	6 signal features from cutting force, vibration, and acoustic emission sensor	Wavelet feature extraction	N/A	67 (2016)
	Tool life estimation	BpNN, Regression Analysis Method	Speed, feed, depth of cut, temperature	N/A	N/A	68 (2002)
Grinding	Monitoring of surface roughness (Ra) and surface shape peak-valley (PV)	IFSVR	Acoustic emission, grinding force, vibration	Identification Model, Fast Fourier transform	85.19% (Ra), 75.93% (PV)	32 (2015)
Drilling	Evaluation of quality and geometric profile (circularity, dimensional error, delamination, surface roughness)	Logical Analysis of Data	Thrust force, cutting force, torque	N/A	94.60%	54 (2015)
Boring	Chatter prediction (stable, transition, chatter)	SVM	Spindle speed, depth of cut, feed rate	Discrete wavelet transform	95%	69 (2017)
Machine Structure	Self-diagnosis and monitoring system	NN, fuzzy logic	Energy (electric power consumption of drive motor, amplitude of amplitude-frequency spectrum of power signal) and acoustic signals	N/A	N/A	70 (1996)
	Prediction of thermal error for compensation	SVR (Gaussian radial basis function kernel), Least square MLR, Least absolute MLR, distributed lag	Temperature of sensitive points (motor, spindle, ambient), deformation of spindle	Fuzzy clustering analysis, gray correlation method	N/A	71 (2013)
	Development of self-optimizing control system, parameter adjustment (tool wear, feed rate)	Fuzzy logic, NN	Cutting force, feed rate, depth of cut, processing time, cutting speed, initial tool wear	N/A	N/A	72 (2014)

Table 1 Continued

Process	Purpose	Algorithms	Input parameters	Preprocessing	Accuracy*	Ref. (Year)
Laser Machining	Predict surface quality, dimensional features and the productivity of laser machined micro-channels	NN, decision trees, K-NN, linear regression	Scanning speed, pulse intensity, pulse frequency	N/A	88.70% (depth - NN), 76.90% (Material removal rate (MRR) - decision tree)	73 (2015)
Abrasive Water Jet	Surface roughness prediction	Extreme machine learning, ANN, GPR	Cutting speed, material thickness, abrasive flow, measurement position	N/A	96.65%	74 (2016)
	Surface roughness prediction	SVM	Traverse speed, water jet pressure, abrasive grit size, abrasive flow rate	GRA	99%	75 (2013)
	Surface roughness prediction	Feed-forward BpNN, regression model	Traverse speed, water jet pressure, stand-off distance, abrasive grit size, abrasive flow rate	N/A	96.99% (NN), 99% (regression)	35 (2008)
Electric Discharge Machining (EDM)	Predict optimum process parameter for minimum wear ratio and maximum MRR	BpNN, particle swarm optimization, simulated annealing, GA	Pulse current, pulse-on time, pulse-off time	N/A	N/A	51 (2015)
	MRR estimation and machining parameter optimization for max MRR	Feed-forward BpNN, GA	Gap voltage, capacitance, feed rate, speed	N/A	96.06%	14 (2010)
	Machining parameter optimization for maximum MRR and minimum surface roughness	GPR, NSGA-II	Mean current, on time, off time	N/A	N/A	47 (2008)
	Machining parameter optimization for maximum MRR and minimum surface roughness	GRA	Cutting radius, on/off time, arc on/off time, servo voltage, wire feed, water flow	N/A	N/A	76 (2006)
Electroche-mical Discharge Machining (ECDM), Electrochemic al Machining (ECM)	Process parameter optimization for maximizing MRR and minimizing radial overcut	TLBO	Electrolyte concentration, electrolyte flow rate, applied voltage, inter-electrode gap,	N/A	18% improvement in MRR	97 (2011)

*Only the accuracies provided by the author/s were included. The accuracy corresponds to the algorithm prediction accuracy compared to the experimental results.

al. monitored the surface roughness and the surface shape peak-valley of the workpiece using interpolation-factor SVM.[32] The acoustic emission, grinding force, and vibration data were used as input parameters.[32]

2.1.4 Drilling

Similarly, product quality predictions were also achieved in the drilling process through monitoring the process parameters, such as thrust force, cutting force, and torque. The circularity, dimensional error, delamination, and surface roughness of machined carbon-fiber-reinforced polymers plates were evaluated using a machine-learning and pattern-recognition method known as logical analysis of data.[54]

2.1.5 Boring

For the boring process, the surface finish quality can be enhanced by preventing chatter. Saravanamurugan et al.[69] studied which parameters, such as the spindle speed, depth of cut and feed rate, generated chatter. Features were extracted from vibration signals using the discrete wavelet transform and classified into stable, transition, or chatter classes using SVM.

2.2 Non-Conventional Machining

Although there have been fewer cases of non-conventional machining processes, learning algorithms were also implemented to improve the finish quality through surface roughness predictions. However, due to the issue of low productivity, one of the main purposes was process parameter optimization for maximizing the

MRR.

2.2.1 Laser Machining

Laser processes are increasingly being used in industrial processes. However, optimized process parameters, especially for sensitive applications such as micromachining, have yet to be found. Teixidor et al.[78] implemented and compared various machine learning algorithms (e.g., linear regression, NN, decision trees and K-NN) in order to predict the surface quality levels, dimensional features, and the productivity rates of laser-machined micro-channels.

The results indicated that the decision trees were more accurate at predicting the MRR, whereas NN were more effective at modeling dimensional features of machined channels.[73]

2.2.2 Abrasive Water Jet

Abrasive water jet machining focuses mainly on surface roughness predictions. This has been achieved mostly through the implementation of various types of NNs, such as feedforward, backpropagation, and extreme machine learning; however, the highest prediction accuracy of 99% was achieved by Deris et al.[75] using a hybrid algorithm that combines grey relational analysis for feature selection and SVM.

2.2.3 Electric Discharge Machining (EDM)

Although there have been efforts to predict the surface roughness for EDM, the main purpose for implementing machine-learning methods was to predict and maximize the MRR. This is mainly due to the low productivity characterized by this process. This task was typically achieved through a combination of both ANNs and EAs,[79] such as BpNN with particle swarm optimization or feedforward BpNN with GA; these EAs were mainly used for optimization purposes.

2.2.4 Electrochemical Machining (ECM)

Due to their similar process characteristics to that of EDM, learning algorithms were also implemented to ECM to predict and maximize the MRR. Rao et al.[97] was able to improve the MRR for ECM using TLBO, which outperformed the artificial bee colony (ABC) algorithm due to the fewer iterations required. TLBO was also implemented to the hybrid process, electrochemical discharge machining, realizing an increase in the MRR of 18% compared to that by the ABC algorithm.

2.3 Machine Structure

Many efforts focused on improving the machining process itself, but the machine tool structure can also be improved in order to achieve self-monitoring or diagnosis and self-adjustments to external disturbances. For instance, Miao et al.[71] developed a thermal error compensation model by studying the relationship between temperatures at sensitive locations and the thermal error generated. From the various algorithms implemented in their study, SVM combined with a fuzzy clustering analysis and the gray correlation method was the most accurate. Park et al.[72] developed a self-optimizing control system that can autonomously adjust process parameters based on the disturbances. In this case, fuzzy logic with a NN is used to predict the tool wear and determine the optimal feed rate.

2.4 Overview and Discussion

As summarized in Table 1, various machine learning algorithms have been implemented to both conventional and non-conventional machining processes for diagnostics and prognostics of machine tools, parameter optimization, and product quality prediction, all of which lead to a more cost-efficient production. It can be observed that the most commonly used algorithms were also those that had the best performances: SVM and ANN. Although these algorithms generally show great performance, its accuracy will highly depend on the input parameters used, obtained from the preprocessing and feature extraction methods. More research focused on these feature extraction techniques will be crucial for practical implementations. ANN and SVR were also implemented for enhancing machine structure, thermal, dynamic characteristics; however, the authors have not provided enough information on the algorithms' performances; the results should be compared with the experimental data in order to determine which algorithm is more appropriate. The case studies reviewed in this paper have mostly been published in the past 5 years, following the trend of the actively researched field of machine learning. Therefore, more cases of machine learning-based machining process can be expected in the future.

3. Future Perspective to Machining Industry

Fig. 2 shows the approximate dates of the major manufacturing paradigms during the last four decades, followed by the accumulated list of technologies. During the 1980s, computer-integrated manufacturing constantly expanded to include flexible manufacturing systems, robotics, and AI.[81]

During this Fourth Industrial Revolution era, these paradigms will increasingly implement machine learning to create a cyber-physical system.

3.1 Case Study of Present and Future Use

The goals of improvements in manufacturing have consistently been in the areas of automation, robotics, and complex analytics to improve efficiency.[82]

With the development of more advanced artificial intelligence in recent years, manufacturing has found a means to push through its limitations. Numerous major corporations in the industry have been investing heavily in the market of smart manufacturing, which is expected to grow by more than $70 billion by 2020.[4]

The implementation of machine learning algorithms to collect and process data in the manufacturing environment has enabled real-time monitoring of equipment to reduce unnecessary waste and increase efficiency at various stages to new heights. For large-scale companies, an "in-house AI development" strategy is used, where the companies both develop and utilize the machine learning tools for manufacturing. This allows for customization of the algorithm to fit the nature of the equipment used in factories. Smaller companies have utilized the alternative strategy of importing software tools from an external source, which requires modification of the programs for integration into the target equipment. One of the companies in the manufacturing industry to have benefited from AI is Siemens.

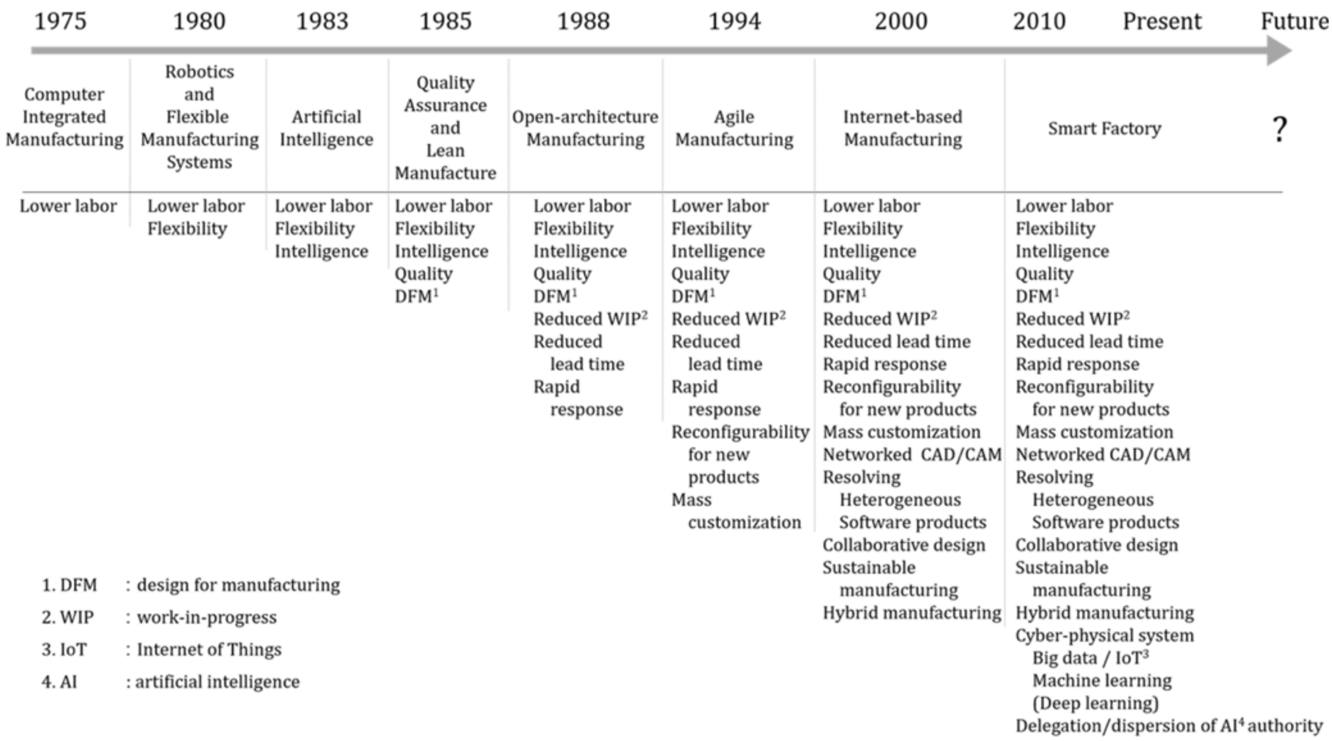

Fig. 2 Major paradigms in manufacturing (modified and updated from reference[81])

Siemens has been using deep learning techniques in conjunction with NN to optimize systems and facilities by analyzing various data and measurement values during operational processes. MindSphere, a cloud-based open-IoT operating system, was developed and distributed by Siemens in 2016 to monitor equipment and enable predictive maintenance by drawing data from a multitude of sources.[83]

The tools were later developed further with the integration of IBM's Watson Analytics, which enhanced performance and reduced downtime.[84]

Another instance in which the integration of AI and NNs has helped improve manufacturing aspects of Siemens was the optimization of nitrous oxide emissions in gas turbines. The AI system in this case was able to reduce the emissions by an additional 10-15% of the optimized solution proposed by engineers.[85]

The latest gas turbines developed by Siemens are equipped with over 500 sensors to collect real-time data on the pressure, temperature, stress, and other variables.[86]

Fig. 3 shows a virtual reality representation of a gas turbine in which the temperature measurements are represented by different colors on the surface. Complex sensor data is translated into colors to give the information meaning. With the installed sensors, real-time data are collected and processed to adjust fuel valves continuously to realize optimal conditions for combustion while accounting for weather conditions and equipment states. In the future, the same technique can be modified and upgraded to implement micro-sensors into machining equipment in the industry. One possible example would be the monitoring and altering of cutting tool parameters based on temperature and wear data collected in real time.[87]

Other companies have also significantly improved the manufacturing processes in their factories by reducing downtime and increasing efficiency levels. GE developed the Brilliant Manufacturing Suite in 2015, which takes a preventative approach to detecting potential problems and inefficiencies by tracking every step of the manufacturing process.[88]

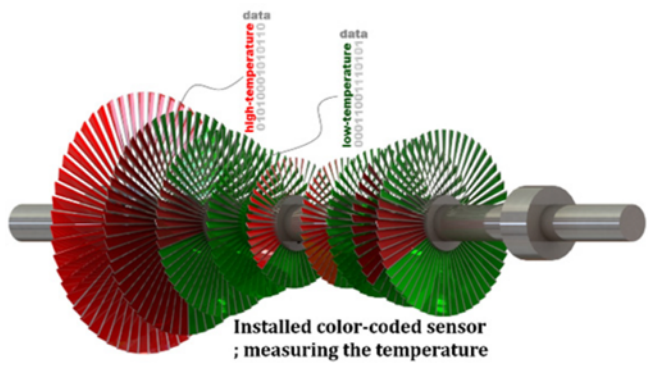

Fig. 3 Virtual reality representation of gas turbine with color-coded temperature sensor data

FANUC used deep reinforcement learning techniques to enable industrial robots to train themselves by performing the same task repetitively until a reasonable level of accuracy is achieved.[89]

Collaborative work between robots and humans can be organized in the future to realize adaptive machining, where humans and robots can modify machining conditions in real time to increase precision and reduce operation times and energy expenditures. Other companies, such as Intel, Kuka, NVIDIA and Microsoft, are also making significant investments in machine-learning-based methodologies to improve manufacturing processes.

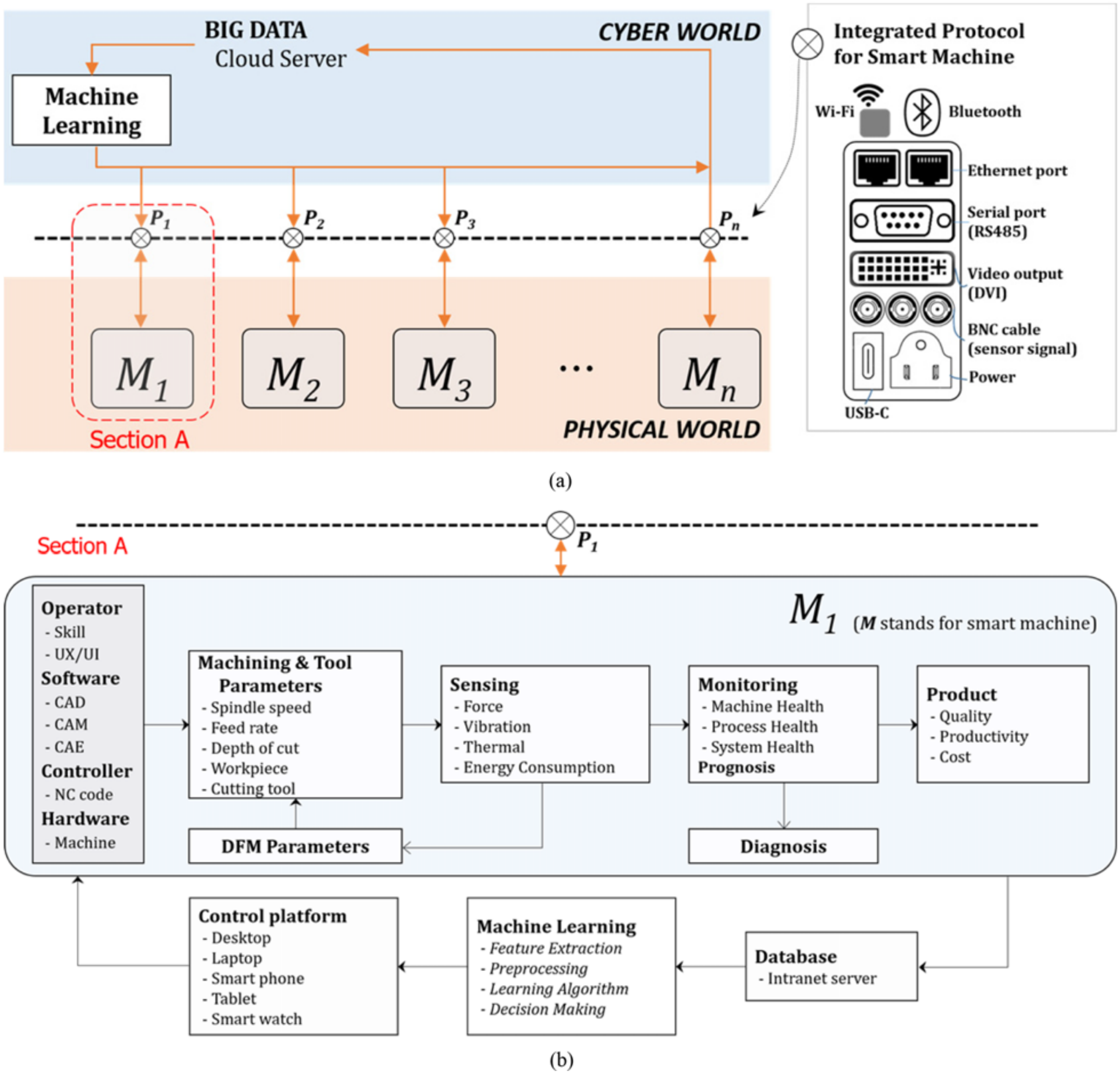

Fig. 4 Conceptual diagram for smart machining (a) outer loop and (b) inner loop

3.2 Smart Machining

The purpose of smart machining is to automate tasks that humans have previously performed in the physical world and to self-optimize the processes of interconnected machines in the cyber world.[19,90-100]

In order to overcome the current limitation in machining, technologies related to artificial intelligence, especially machine-learning techniques, are being implemented.

The conceptual architecture for smart machining is structured as shown in Fig. 4(a) represents the process for establishing a connection between the cyber and physical worlds. Machine-to-machine and machine-to-server communications are enabled through an integrated protocol. In Fig. 4(b), a single machining process composed of machining, sensing, monitoring, and diagnosis is shown. The data obtained from these processes is sent to a cloud server through the integrated protocol.

The core technologies for smart machining are as follows:

· Enhancement of sensor analysis technology and sensor networks

· Development and integration of communication protocols for smart machines

· Application and development of machine learning algorithm and preprocessing methods for machining processes

· Operation and management know-how accumulation

· Data acquisition of machine structures, machining processes, products, and related parameters - big data

Fig. 5 shows a concept of smart hybrid manufacturing system that performs various subtractive and additive manufacturing processes on a single platform. Various sensors, such as force, vibration, displacement, temperature, humidity, acceleration, and energy consumption sensors, are embedded in the system, obtaining these data in real-time. By dispersing the artificial intelligence authority based on the environment and communication, optimized data on various levels can be provided. Level 1 is the lowest level that consists of sensor

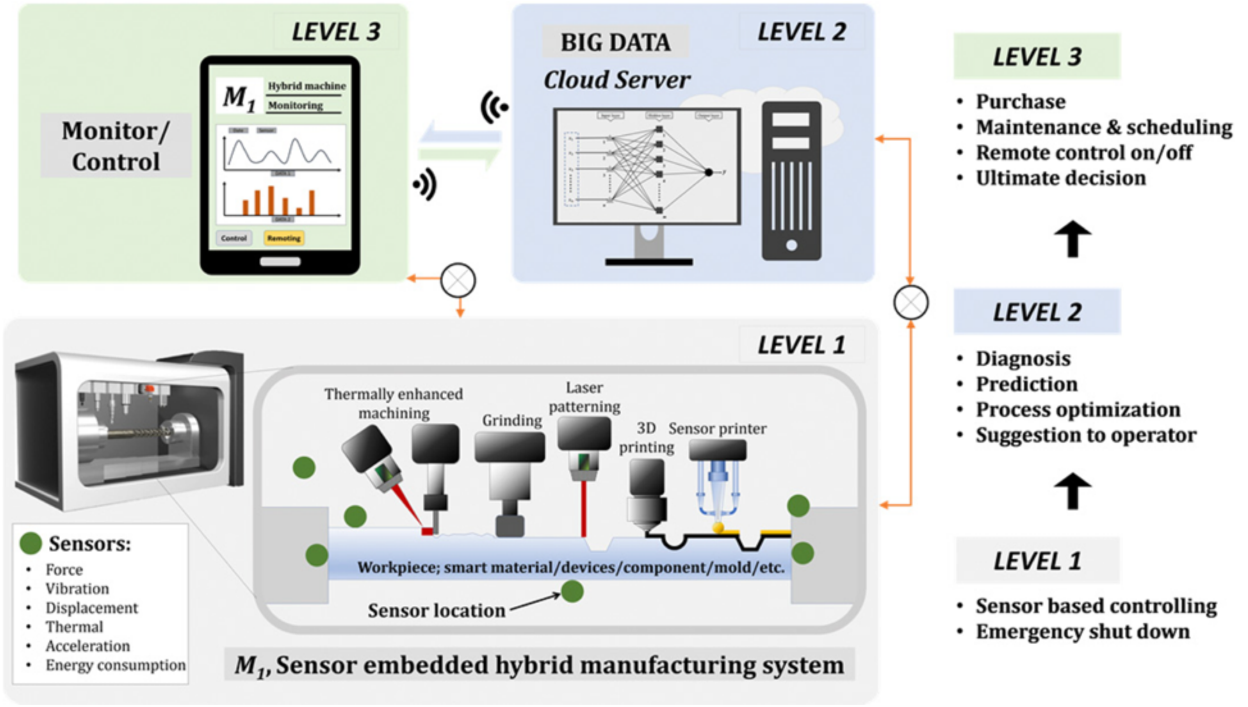

Fig. 5 Smart hybrid manufacturing system

based control and emergency shutdown. In level 2, data is collected on a cloud server, creating a big data environment. Based on the data, artificial intelligence and machine learning can be used for diagnosis, prediction, and process optimization, providing the solutions to the user or operator. Level 3 is the highest level of authority. Based on the solutions provided in the level 2, the machine can make final decisions on purchasing, scheduling, and maintenance, while also having the overall authority for controlling and operating the machine.

3.3 Challenges in Practice

With advances in sensing, communication and computing technologies, machine learning has a great potential to dramatically improve the efficiency of various machining processes as previously mentioned. However, the integration of physical processes, computing, and networking in manufacturing systems presents unique challenges about safety and security, among others. Thus, there is a strong need for new machine learning algorithms, which are specific to manufacturing systems and machining processes to address these issues.

Guaranteeing safety is a fundamentally important factor in any machining process, particularly when humans are involved. However, a naive application of several machine learning algorithms threatens safety because the obtained results often have no performance guarantees.[101] Thus, it is not unlikely that the decision made based on learning methods drives a machining process into an unsafe range of operation. Such a safety issue is particularly serious when using reinforcement learning, which induces a machine or tool to explore to improve its decision quality or performance; the machine can encounter unsafe situations in the process of exploration. To resolve this issue, several safe learning methods have recently been proposed by using constrained-optimization,[102,103] reachability,[104] and Lyapunov stability.[105] It is an important future research to develop safe learning algorithms specific to machining processes based on the domain knowledge of machining.

Security is another critical issue in smart machining processes. As machines and tools are connected through communication networks, external malicious attacks, such as hacking, can disrupt whole manufacturing processes, for example, by injecting corrupted sensor data. Furthermore, it has recently been demonstrated that many popular machine learning methods, such as deep learning, are vulnerable to a negligible modification of input data, which could be conducted by an attacker.[106,107] To address the security issue at the infrastructure level, smart manufacturing systems must be equipped with a proper countermeasure, which is an active area of research in cyber-physical systems community.[108] More importantly, at the algorithmic level, secure machine learning methods are desirable to fundamentally alleviate the impact of manipulated input data on smart machining processes.[109]

4. Conclusions

Machine learning algorithms applied to machining processes were classified according to the machining type and process characteristics in this paper. Different cases of smart machining processes were summarized and reviewed. The core technologies for smart machining were also suggested. As mentioned above, many industries are researching and using machine learning to enhance their current processes. The efficiency of the machining industry will greatly improve as they shift towards smart machining processes, ultimately achieving self-optimization and adaptation to uncontrollable variables. However, it is important to consider the safety and security issues that come with the implementation of such smart processes and thus the countermeasures must be taken into account.

ACKNOWLEDGEMENT

This research was supported by the Basic Research Lab Program through the National Research Foundation of Korea (NRF) funded by the MSIT (2018R1A4A1059976), the SNU-Hojeon Garment Smart Factory Research Center funded by Hojeon Ltd., Korea Basic Science Institute (KBSI) Creative Convergence Research Project (CAP-PN2017003) funded by the National Research Council of Science and Technology (NST) in Korea, Creative-Pioneering Researchers Program through Seoul National University and Future Research Committee funded by Seoul National University in Korea.

REFERENCES

1. Shrouf, F., Ordieres, J., and Miragliotta, G., “Smart Factories in Industry 4.0: A Review of the Concept and of Energy Management Approached in Production Based on the Internet of Things Paradigm,” Proc. of IEEE International Conference on Industrial Engineering and Engineering Management, pp. 697-701, 2014.
2. Yan, J., Meng, Y., Lu, L., and Guo, C., “Big-Data-Driven Based Intelligent Prognostics Scheme in Industry 4.0 Environment,” Proc. of Prognostics and System Health Management Conference (PHM-Harbin), pp. 1-5, 2017.
3. Coulter, R. and Pan, L., “Intelligent Agents Defending for an IoT World: A Review,” Computers & Security, Vol. 73, pp. 439-458, 2018.
4. TrendForce, “TrendForce Forecasts Size of Global Market for Smart Manufacturing Solutions to Top US$320 Billion by 2020; Product Development Favors Integrated Solutions,” https://press.trendforce.com/press/20170731-2911.html (Accessed 8 AUG 2018)
5. Antony, P., Jnanesh, N., and Prajna, M., “Machine Learning Models for Material Selection: Framework for Predicting Flatwise Compressive Strength Using Ann,” Proc. of 2nd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), pp. 424-427, 2016.
6. Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., et al., “Smart Manufacturing: Past Research, Present Findings, and Future Directions,” International Journal of Precision Engineering and Manufacturing-Green Technology, Vol. 3, No. 1, pp. 111-128, 2016.
7. Beier, G., Niehoff, S., Ziems, T., and Xue, B., “Sustainability Aspects of a Digitalized Industry–A Comparative Study from China and Germany,” International Journal of Precision Engineering and Manufacturing-Green Technology, Vol. 4, No. 2, pp. 227-234, 2017.
8. Arisoy, Y. M. and Özel, T., “Machine Learning Based Predictive Modeling of Machining Induced Microhardness and Grain Size in Ti–6Al–4V Alloy,” Materials and Manufacturing Processes, Vol. 30, No. 4, pp. 425-433, 2015.
9. Wen, L., Li, X., Gao, L., and Zhang, Y., “A New Convolutional Neural Network-Based Data-Driven Fault Diagnosis Method,” IEEE Transactions on Industrial Electronics, Vol. 65, No. 7, pp. 5990-5998, 2018.
10. Benkedjouh, T., Medjaher, K., Zerhouni, N., and Rechak, S., “Health Assessment and Life Prediction of Cutting Tools Based on Support Vector Regression,” Journal of Intelligent Manufacturing, Vol. 26, No. 2, pp. 213-223, 2015.
11. Bergmann, S., Feldkamp, N., and Strassburger, S., “Emulation of Control Strategies through Machine Learning in Manufacturing Simulations,” Journal of Simulation, Vol. 11, No. 1, pp. 38-50, 2017.
12. Cho, S. J. and Kang, S. H., “Industrial Applications of Machine Learning (Artificial Intelligence),” Korean Institute Industrial Engineers ie Magazine, Vol. 23, No. 2, pp. 34-38, 2016.
13. Pontes, F. J., de Paiva, A. P., Balestrassi, P. P., Ferreira, J. R., and da Silva, M. B., “Optimization of Radial Basis Function Neural Network Employed for Prediction of Surface Roughness in Hard Turning Process Using Taguchi’s Orthogonal Arrays,” Expert Systems with Applications, Vol. 39, No. 9, pp. 7776-7787, 2012.
14. Somashekhar, K. P., Ramachandran, N., and Mathew, J., “Optimization of Material Removal Rate in Micro-EDM Using Artificial Neural Network and Genetic Algorithms,” Materials and Manufacturing Processes, Vol. 25, No. 6, pp. 467-475, 2010.
15. Wuest, T., Irgens, C., and Thoben, K.-D., “An Approach to Monitoring Quality In Manufacturing Using Supervised Machine Learning on Product State Data,” Journal of Intelligent Manufacturing, Vol. 25, No. 5, pp. 1167-1180, 2014.
16. Le Cun, Y., Bengio, Y., and Hinton, G., “Deep Learning,” Nature, Vol. 521, No. 7553, pp. 436-444, 2015.
17. Schmidhuber, J., “Deep Learning in Neural Networks: An Overview,” Neural Networks, Vol. 61, pp. 85-117, 2015.
18. Vahabli, E. and Rahmati, S., “Application of an RBF Neural Network for FDM Parts’ Surface Roughness Prediction for Enhancing Surface Quality,” International Journal of Precision Engineering and Manufacturing, Vol. 17, No. 12, pp. 1589-1603, 2016.
19. Mekid, S., Pruschek, P., and Hernandez, J., “Beyond Intelligent Manufacturing: A New Generation of Flexible Intelligent NC Machines,” Mechanism and Machine Theory, Vol. 44, No. 2, pp. 466-476, 2009.
20. Szkilnyk, G., Hughes, K., and Surgenor, B., “Vision Based Fault Detection of Automated Assembly Equipment,” Proc. of International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, pp. 691-697, 2011.
21. Tüfekci, P., “Prediction of Full Load Electrical Power Output of a Base Load Operated Combined Cycle Power Plant Using Machine Learning Methods,” International Journal of Electrical Power & Energy Systems, Vol. 60, pp. 126-140, 2014.

22. Kroll, B., Schaffranek, D., Schriegel, S., and Niggemann, O., “System Modeling Based on Machine Learning for Anomaly Detection and Predictive Maintenance in Industrial Plants,” Proc. of IEEE Emerging Technology and Factory Automation (ETFA), pp. 1-7, 2014.

23. Elforjani, M. and Shanbr, S., “Prognosis of Bearing Acoustic Emission Signals Using Supervised Machine Learning,” IEEE Transactions on Industrial Electronics, Vol. 65, No. 7, pp. 5864-5871, 2018.

24. Pinto, A. M., Rocha, L. F., and Moreira, A. P., “Object Recognition Using Laser Range Finder and Machine Learning Techniques,” Robotics and Computer-Integrated Manufacturing, Vol. 29, No. 1, pp. 12-22, 2013.

25. Tsai, M.-S., Yen, C.-L., and Yau, H.-T., “Integration of an Empirical Mode Decomposition Algorithm with Iterative Learning Control for High-Precision Machining,” IEEE/ASME Transactions on Mechatronics, Vol. 18, No. 3, pp. 878-886, 2013.

26. Sumesh, A., Rameshkumar, K., Mohandas, K., and Babu, R. S., “Use of Machine Learning Algorithms for Weld Quality Monitoring Using Acoustic Signature,” Procedia Computer Science, Vol. 50, No. pp. 316-322, 2015.

27. Yiakopoulos, C., Gryllias, K. C., and Antoniadis, I. A., “Rolling Element Bearing Fault Detection in Industrial Environments Based on a K-Means Clustering Approach,” Expert Systems with Applications, Vol. 38, No. 3, pp. 2888-2911, 2011.

28. Chu, W.-S., Kim, M.-S., Jang, K.-H., Song, J.-H., Rodrigue, H., et al., “From Design for Manufacturing (DFM) to Manufacturing for Design (MFD) via Hybrid Manufacturing and Smart Factory: A Review and Perspective of Paradigm Shift,” International Journal of Precision Engineering and Manufacturing-Green Technology, Vol. 3, No. 2, pp. 209-222, 2016.

29. Chu, W.-S., Kim, C.-S., Lee, H.-T., Choi, J.-O., Park, J.-I., et al “Hybrid Manufacturing in Micro/Nano Scale: A Review,” International Journal of Precision Engineering and Manufacturing-Green Technology, Vol. 1, No. 1, pp. 75-92, 2014.

30. Lu, X., Hu, X., Wang, H., Si, L., Liu, Y., and Gao, L., “Research on the Prediction Model of Micro-Milling Surface Roughness of Inconel718 Based on SVM,” Industrial Lubrication and Tribology, Vol. 68, No. 2, pp. 206-211, 2016.

31. Peng, C., Wang, L., and Liao, T. W., “A New Method for the Prediction of Chatter Stability Lobes Based on Dynamic Cutting Force Simulation Model and Support Vector Machine,” Journal of Sound and Vibration, Vol. 354, pp. 118-131, 2015.

32. Zhang, D., Bi, G., Sun, Z., and Guo, Y., “Online Monitoring of Precision Optics Grinding Using Acoustic Emission Based on Support Vector Machine,” The International Journal of Advanced Manufacturing Technology, Vol. 80, Nos. 5-8, pp. 761-774, 2015.

33. Deng, S., Xu, Y., Li, L., Li, X., and He, Y., “A Feature-Selection Algorithm Based on Support Vector Machine-Multiclass for Hyperspectral Visible Spectral Analysis,” Journal of Food Engineering, Vol. 119, No. 1, pp. 159-166, 2013.

34. Demetgul, M., “Fault Diagnosis on Production Systems with Support Vector Machine and Decision Trees Algorithms,” The International Journal of Advanced Manufacturing Technology, Vol. 67, Nos. 9-12, pp. 2183-2194, 2013.

35. Çaydaş, U. and Hascalık, A., “A Study on Surface Roughness in Abrasive Waterjet Machining Process Using Artificial Neural Networks and Regression Analysis Method,” Journal of Materials Processing Technology, Vol. 202, Nos. 1-3, pp. 574-582, 2008.

36. Laha, D., Ren, Y., and Suganthan, P. N., “Modeling of Steelmaking Process with Effective Machine Learning Techniques,” Expert Systems with Applications, Vol. 42, No. 10, pp. 4687-4696, 2015.

37. Yuan, Y., Zhang, H.-T., Wu, Y., Zhu, T., and Ding, H., “Bayesian Learning-Based Model-Predictive Vibration Control for Thin-Walled Workpiece Machining Processes,” IEEE/ASME Transactions on Mechatronics, Vol. 22, No. 1, pp. 509-520, 2017.

38. Lu, Y., Rajora, M., Zou, P., and Liang, S. Y., “Physics-Embedded Machine Learning: Case Study with Electrochemical Micro-Machining,” Machines, Vol. 5, No. 1, Paper No. 4, 2017.

39. Jia, F., Lei, Y., Lin, J., Zhou, X., and Lu, N., “Deep Neural Networks: A Promising Tool for Fault Characteristic Mining and Intelligent Diagnosis of Rotating Machinery with Massive Data,” Mechanical Systems and Signal Processing, Vol. 72, pp. 303-315, 2016.

40. Tan, S. C., Watada, J., Ibrahim, Z., and Khalid, M., “Evolutionary Fuzzy ARTMAP Neural Networks for Classification of Semiconductor Defects,” IEEE Transactions on Neural Networks and Learning Systems, Vol. 26, No. 5, pp. 933-950, 2015.

41. Sukthomya, W. and Tannock, J., “The Optimisation of Neural Network Parameters Using Taguchi’s Design of Experiments Approach: An Application in Manufacturing Process Modelling,” Neural Computing & Applications, Vol. 14, No. 4, pp. 337-344, 2005.

42. Taga, Ö., Kiral, Z., and Yaman, K., “Determination of Cutting Parameters in End Milling Operation Based on the Optical Surface Roughness Measurement,” International Journal of Precision Engineering and Manufacturing, Vol. 17, No. 5, pp. 579-589, 2016.

43. Jang, D.-Y., Jung, J., and Seok, J., “Modeling and Parameter Optimization for Cutting Energy Reduction in MQL Milling Process,” International Journal of Precision Engineering and Manufacturing-Green Technology, Vol. 3, No. 1, pp. 5-12, 2016.

44. Huang, P. B., Ma, C.-C., and Kuo, C.-H., “A PNN Self-Learning Tool Breakage Detection System in End Milling Operations,” Applied Soft Computing, Vol. 37, pp. 114-124, 2015.

45. Pontes, F. J., Ferreira, J. R., Silva, M. B., Paiva, A. P., and Balestrassi, P. P., “Artificial Neural Networks for Machining Processes Surface Roughness Modeling,” The International Journal of Advanced Manufacturing Technology, Vol. 49, Nos. 9-12, pp. 879-902, 2010.

46. Le, C. V., Pang, C. K., Gan, O. P., Chee, X. M., Zhang, D. H., et al., "Classification of Energy Consumption Patterns for Energy Audit and Machine Scheduling in Industrial Manufacturing Systems," Transactions of the Institute of Measurement and Control, Vol. 35, No. 5, pp. 583-592, 2013.

47. Yuan, J., Wang, K., Yu, T., and Fang, M., "Reliable Multi-Objective Optimization of High-Speed WEDM Process Based on Gaussian Process Regression," International Journal of Machine Tools and Manufacture, Vol. 48, No. 1, pp. 47-60, 2008.

48. Kupp, N., Huang, K., Carulli, J., and Makris, Y., "Spatial Estimation of Wafer Measurement Parameters Using Gaussian Process Models," Proc. of 2012 IEEE International Test Conference, pp. 1-8, 2012.

49. Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T., "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," IEEE Transactions on Evolutionary Computation, Vol. 6, No. 2, pp. 182-197, 2002.

50. Su, M.-S., Chia, C.-C., Chen, C.-Y., and Chen, J.-F., "Classification of Partial Discharge Events in GILBS Using Probabilistic Neural Networks and the Fuzzy C-Means Clustering Approach," International Journal of Electrical Power & Energy Systems, Vol. 61, pp. 173-179, 2014.

51. Majumder, A., "Comparative Study of Three Evolutionary Algorithms Coupled with Neural Network Model for Optimization of Electric Discharge Machining Process Parameters," Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, Vol. 229, No. 9, pp. 1504-1516, 2015.

52. Polczynski, M. and Kochanski, A., "Knowledge Discovery and Analysis in Manufacturing," Quality Engineering, Vol. 22, No. 3, pp. 169-181, 2010.

53. Lin, W., Yu, D., Wang, S., Zhang, C., Zhang, S., et al., "Multi-Objective Teaching–Learning-Based Optimization Algorithm for Reducing Carbon Emissions and Operation Time in Turning Operations," Engineering Optimization, Vol. 47, No. 7, pp. 994-1007, 2015.

54. Shaban, Y., Yacout, S., Balazinski, M., Meshreki, M., and Attia, H., "Diagnosis of Machining Outcomes Based on Machine Learning with Logical Analysis of Data," Proc. of International Conference on Industrial Engineering and Operations Management (IEOM), pp. 1-8, 2015.

55. García-Ordás, M., "Wear Characterization of the Cutting Tool in Milling Processes Using Shape and Texture Descriptors," Ph.D. Thesis, Universidad de León, 2017.

56. Cho, S., Asfour, S., Onar, A., and Kaundinya, N., "Tool Breakage Detection Using Support Vector Machine Learning in a Milling Process," International Journal of Machine Tools and Manufacture, Vol. 45, No. 3, pp. 241-249, 2005.

57. Wu, D., Jennings, C., Terpenny, J., Gao, R. X., and Kumara, S., "A Comparative Study on Machine Learning Algorithms for Smart Manufacturing: Tool Wear Prediction Using Random Forests," Journal of Manufacturing Science and Engineering, Vol. 139, No. 7, Paper No. 071018, 2017.

58. Park, J., Law, K. H., Bhinge, R., Biswas, N., Srinivasan, A., et al., "A Generalized Data-Driven Energy Prediction Model with Uncertainty for a Milling Machine Tool Using Gaussian Process," Proc. of American Society of Mechanical Engineers on International Manufacturing Science and Engineering Conference, Vol. 2, Paper No. MSEC2015-9354, 2015.

59. Bhinge, R., Biswas, N., Dornfeld, D., Park, J., Law, K. H., et al., "An Intelligent Machine Monitoring System for Energy Prediction Using a Gaussian Process Regression," Proc. of IEEE International Conference on Big Data, pp. 978-986, 2014.

60. Klancnik, S., Brezocnik, M., and Balic, J., "Intelligent CAD/CAM System for Programming of CNC Machine Tools," International Journal of Simulation Modeling, Vol. 15, No. 1, pp. 109-120, 2016.

61. Krishnakumar, P., Rameshkumar, K., and Ramachandran, K., "Tool Wear Condition Prediction Using Vibration Signals in High Speed Machining (HSM) of Titanium (Ti-6Al-4V) Alloy," Procedia Computer Science, Vol. 50, pp. 270-275, 2015.

62. Arnold, F., Hänel, A., Nestler, A., and Brosius, A., "New Approaches for the Determination of Specific Values for Process Models in Machining Using Artificial Neural Networks," Procedia Manufacturing, Vol. 11, pp. 1463-1470, 2017.

63. Elangovan, M., Sakthivel, N., Saravanamurugan, S., Nair, B. B., and Sugumaran, V., "Machine Learning Approach to the Prediction of Surface Roughness Using Statistical Features of Vibration Signal Acquired in Turning," Procedia Computer Science, Vol. 50, pp. 282-288, 2015.

64. Jurkovic, Z., Cukor, G., Brezocnik, M., and Brajkovic, T., "A Comparison of Machine Learning Methods for Cutting Parameters Prediction in High Speed Turning Process," Journal of Intelligent Manufacturing, 2016. (DOI: 10.1007/s10845-016-1206-1)

65. D'Addona, D. M., Ullah, A. S., and Matarazzo, D., "Tool-Wear Prediction and Pattern-Recognition Using Artificial Neural Network and DNA-Based Computing," Journal of Intelligent Manufacturing, Vol. 28, No. 6, pp. 1285-1301, 2017.

66. Painuli, S., Elangovan, M., and Sugumaran, V., "Tool Condition Monitoring Using K-Star Algorithm," Expert Systems with Applications, Vol. 41, No. 6, pp. 2638-2643, 2014.

67. Karam, S., Centobelli, P., D'Addona, D. M., and Teti, R., "Online Prediction of Cutting Tool Life in Turning via Cognitive Decision Making," Procedia CIRP, Vol. 41, pp. 927-932, 2016.

68. Tosun, N. and Özler, L., "A Study of Tool Life in Hot Machining Using Artificial Neural Networks and Regression Analysis Method," Journal of Materials Processing Technology, Vol. 124, Nos. 1-2, pp. 99-104, 2002.

69. Saravanamurugan, S., Thiyagu, S., Sakthivel, N., and Nair, B. B., "Chatter Prediction in Boring Process Using Machine Learning

Technique," International Journal of Manufacturing Research, Vol. 12, No. 4, pp. 405-422, 2017.

70. Jędrzejewski, J. and Kwaśny, W., "Artificial Intelligence Tools in Diagnostics of Machine Tool Drives," CIRP Annals, Vol. 45, No. 1, pp. 411-414, 1996.

71. Miao, E.-M., Gong, Y.-Y., Niu, P.-C., Ji, C.-Z., and Chen, H.-D., "Robustness of Thermal Error Compensation Modeling Models of CNC Machine Tools," The International Journal of Advanced Manufacturing Technology, Vol. 69, Nos. 9-12, pp. 2593-2603, 2013.

72. Park, H.-S. and Tran, N.-H., "Development of a Smart Machining System Using Self-Optimizing Control," The International Journal of Advanced Manufacturing Technology, Vol. 74, Nos. 9-12, pp. 1365-1380, 2014.

73. Teixidor, D., Grzenda, M., Bustillo, A., and Ciurana, J., "Modeling Pulsed Laser Micromachining of Micro Geometries Using Machine-Learning Techniques," Journal of Intelligent Manufacturing, Vol. 26, No. 4, pp. 801-814, 2015.

74. Ćojbašić, Ž., Petković, D., Shamshirband, S., Tong, C. W., Ch, S., et al., "Surface Roughness Prediction by Extreme Learning Machine Constructed with Abrasive Water Jet," Precision Engineering, Vol. 43, pp. 86-92, 2016.

75. Deris, A. M., Zain, A. M., and Sallehuddin, R., "Hybrid GR-SVM for Prediction of Surface Roughness in Abrasive Water Jet Machining," Meccanica, Vol. 48, No. 8, pp. 1937-1945, 2013.

76. Chiang, K.-T. and Chang, F.-P., "Optimization of the WEDM Process of Particle-Reinforced Material with Multiple Performance Characteristics Using Grey Relational Analysis," Journal of Materials Processing Technology, Vol. 180, Nos. 1-3, pp. 96-101, 2006.

77. Mellal, M. A. and Williams, E. J., "Parameter Optimization of Advanced Machining Processes Using Cuckoo Optimization Algorithm and Hoopoe Heuristic," Journal of Intelligent Manufacturing, Vol. 27, No. 5, pp. 927-942, 2016.

78. Ullah, S. M. S., Muhammad, I., and Ko, T. J., "Optimal Strategy to Deal with Decision Making Problems in Machine Tools Remanufacturing," International Journal of Precision Engineering and Manufacturing-Green Technology, Vol. 3, No. 1, pp. 19-26, 2016.

79. Panda, B. N., Bahubalendruni, M. R., and Biswal, B. B., "A General Regression Neural Network Approach for the Evaluation of Compressive Strength of FDM Prototypes," Neural Computing and Applications, Vol. 26, No. 5, pp. 1129-1136, 2015.

80. Kıran, M. S. and Fındık, O., "A Directed Artificial Bee Colony Algorithm," Applied Soft Computing, Vol. 26, pp. 454-462, 2015.

81. Wright, P. K., "21st Century Manufacturing," Prentice Hall Upper Saddle River, 2001.

82. Walker, J., "Machine Learning in Manufacturing – Present and Future Use-Cases," https://www.techemergence.com/machine-learning-in-manufacturing/ (Accessed 8 AUG 2018)

83. Busch, R., "Artificial Intelligence: Optimizing Industrial Operations," https://www.siemens.com/innovation/en/home/pictures-of-the-future/industry-and-automation/the-future-of manufacturing-ai-in-industry.html, 2017, (Accessed 31 January).

84. Petry, D., "Siemens and IBM to bring Watson Analytics to MindSphere," https://www.siemens.com/press/en/pressrelease/?press=/en/pressrelease/2016/digitalfactory/pr2016120102dfen.htm (Accessed 8 AUG 2018)

85. Pease, A. F., "Tomorrow's Information Factories," https://www.siemens.com/global/en/home/company/innovation/pictures-of-the-future/fom.html (Accessed 8 AUG 2018)

86. Gold, S., "How to Step inside a Gas Turbine," https://www.siemens.com/innovation/en/home/pictures-of-the-future/digitalization-and-software/simulation-and-virtual-reality-simulations-gas-turbines.html (Accessed 8 AUG 2018)

87. Trsek, H., "Isochronous Wireless Network for Real-Time Communication in Industrial Automation," Springer, 2016.

88. GE Imagination at Work, "GE Launches Brilliant Manufacturing Suite to Help Manufacturers Increase Production Efficiency, Execution and Optimization through Advanced Analytics," https://www.ge.com/digital/press-releases/ge-launches-brilliant-manufacturing-suite (Accessed 8 AUG 2018)

89. Knight, W., "This Factory Robot Learns a New Job Overnight," https://www.technologyreview.com/s/601045/this-factory-robot-learns-a-new-job-overnight/ (Accessed 8 AUG 2018)

90. Peukert, B., Benecke, S., Clavell, J., Neugebauer, S., Nissen, N. F., et al., "Addressing Sustainability and Flexibility in Manufacturing via Smart Modular Machine Tool Frames to Support Sustainable Value Creation," Procedia CIRP, Vol. 29, pp. 514-519, 2015.

91. Yoon, H.-S., Lee, H.-T., Jang, K.-H., Kim, C.-S., Park, H., et al., "CAD/CAM for Scalable Nanomanufacturing: A Network-Based System for Hybrid 3D Printing," Microsystems & Nanoengineering, Vol. 3, Paper No. 17072, 2017.

92. Cao, H., Zhang, X., and Chen, X., "The Concept and Progress of Intelligent Spindles: A Review," International Journal of Machine Tools and Manufacture, Vol. 112, pp. 21-52, 2017.

93. Chen, T.-C., Chen, Y.-J., Hung, M.-H., and Hung, J.-P., "Design Analysis of Machine Tool Structure with Artificial Granite Material," Advances in Mechanical Engineering, Vol. 8, No. 7, pp. 1-14, 2016. (DOI: 10.1177/1687814016656533)

94. Park, H.-S., Qi, B., Dang, D.-V., and Park, D. Y., "Development of Smart Machining System for Optimizing Feedrates to Minimize Machining Time," Journal of Computational Design and Engineering, Vol. 5, No. 3, pp. 299-304, 2017.

95. Jędrzejewski, J. and Kwaśny, W., "Discussion of Machine Tool Intelligence, Based on Selected Concepts and Research," Journal of Machine Engineering, Vol. 15, No. 4, pp. 5-26, 2015.

96. Tapoglou, N., Mehnen, J., Butans, J., and Morar, N. I., "Online On-Board Optimization of Cutting Parameter for Energy Efficient CNC Milling," Procedia CIRP, Vol. 40, pp. 384-389, 2016.

97. Rao, R. V. and Kalyankar, V., "Parameters Optimization of Advanced Machining Processes Using TLBO Algorithm," International Conference on Engineering, Project, and Production Management (EPPM), Singapore, Science Direct, pp. 20-21, 2011.

98. Gao, S. and Huang, H., "Recent Advances in Micro-And Nano-Machining Technologies," Frontiers of Mechanical Engineering, Vol. 12, No. 1, pp. 18-32, 2017.

99. Fujishima, M., Mori, M., Nishimura, K., and Ohno, K., "Study on Quality Improvement of Machine Tools," Procedia CIRP, Vol. 59, pp. 156-159, 2017.

100. Ahn, S. H., Sundararajan, V., Smith, C., Kannan, B., D'Souza, R., et al., "Cybercut: An Internet-Based CAD/CAM System," Journal of Computing and Information Science in Engineering, Vol. 1, No. 1, pp. 52-59, 2001.

101. Garcıa, J. and Fernández, F., "A Comprehensive Survey on Safe Reinforcement Learning," Journal of Machine Learning Research, Vol. 16, No. 1, pp. 1437-1480, 2015.

102. Achiam, J., Held, D., Tamar, A., and Abbeel, P., "Constrained Policy Optimization," arXiv preprint arXiv:1705.10528, 2017.

103. Aswani, A., Gonzalez, H., Sastry, S. S., and Tomlin, C., "Provably Safe and Robust Learning-Based Model Predictive Control," Automatica, Vol. 49, No. 5, pp. 1216-1226, 2013.

104. Akametalu, A. K., Kaynama, S., Fisac, J. F., Zeilinger, M. N., Gillula, J. H., et al., "Reachability-Based Safe Learning with Gaussian Processes," Proc. of the 53rd IEEE Conference on Decision and Control, pp. 1424-1431, 2014.

105. Berkenkamp, F., Turchetta, M., Schoellig, A., and Krause, A., "Safe Model-Based Reinforcement Learning with Stability Guarantees," Advances in Neural Information Processing Systems, pp. 908-918, 2017.

106. Madry, A., Makelov, A., Schmidt, L., Tsipras, D., and Vladu, A., "Towards Deep Learning Models Resistant to Adversarial Attacks," arXiv preprint arXiv:1706.06083, 2017.

107. Papernot, N., McDaniel, P., Jha, S., Fredrikson, M., Celik, Z. B., et al., "The Limitations of Deep Learning in Adversarial Settings," Proc. of IEEE European Symposium on Security and Privacy (EuroS&P), pp. 372-387, 2016.

108. Humayed, A., Lin, J., Li, F., and Luo, B., "Cyber-Physical Systems Security—A Survey," IEEE Internet of Things Journal, Vol. 4, No. 6, pp. 1802-1831, 2017.

109. Barreno, M., Nelson, B., Joseph, A. D., and Tygar, J., "The Security of Machine Learning," Machine Learning, Vol. 81, No. 2, pp. 121-148, 2010.