Digitalisation and servitisation of machine tools in the era of Industry 4.0: a review

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Abstract

Machine tools play a pivotal role in the manufacturing world since their performance significantly affects the product quality and production efficiency. In the era of Industry 4.0, machine tools are expected to have a higher level of accessibility, connectivity, intelligence, adaptivity, and autonomy. With the rapid development and application of various Industry 4.0 technologies, digitalisation and servitisation of machine tools have become a new research trend. However, few review articles on the development of machine tools in the context of Industry 4.0 have been reported. To understand the current status of digitalisation and servitisation of machine tools, this paper provides a systematic literature review combining both bibliometric and qualitative analysis. Our review results provide a comprehensive and in-depth understanding of recent advancements of digitalisation and servitisation of machine tools, including the key enabling technologies, methods, standards, architectures, and applications. Furthermore, we propose a novel conceptual framework of Cyber-Physical Machine Tool (CPMT) as a systematic approach to achieving digitalisation and servitisation of next-generation machine tools. Finally, major research issues, challenges, and future research directions are discussed. This work will help researchers and industrial practitioners spark new ideas for developing the next-generation machine tools in the era of Industry 4.0.

Key words: machine tools; industry 4.0; smart manufacturing; digitalisation; servitisation.

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Nomenclature

AE	Acoustic Emission	ICT	Information and Communication Technology
AGV	Automated Guided Vehicle	IIoT	Industrial Internet of Things
AI	Artificial Intelligence	IoS	Internet of Services
AMQP	Advanced Message Queuing Protocol	IoT	Internet of Things
ANFIS	Adaptive neuro fuzzy inference system	IT	Information Technology
ANN	Artificial Neural Networks	KNN	K-Nearest Neighbors
AR	Augmented Reality	LSTM	Long Short-Term Memory
BPNN	Back propagation neural network	M2M	Machine-to-Machine
CAPP	Computer Aided Process Planning	MCP	Machining Capability Profile
CCD	Charge-Coupled Device	MES	Manufacturing Execution System
CMOS	Complementary Metal Oxide Semiconductor	ML	Machine Learning
CNC	Computer Numerical Control	MQTT	Message Queuing Telemetry Transport
CNN	Convolutional Neural Network	MTDT	Machine Tool Digital Twin
CoAP	Constrained Application Protocol	OWL	Ontology Web Language
CPMT	Cyber-Physical Machine Tool	PCA	Principal Component Analysis
CPPS	Cyber-Physical Production Systems	PHM	Prognostics and Health Management
CPS	Cyber-Physical Systems	PLC	Programmable Logic Controller
DBN	Deep Belief Network	PSO	Particle Swarm Optimization
DBSCAN	Density-based spatial clustering of applications with noise	RBF	Radial basis function
DDPG	Deep Deterministic Policy Gradient	RF	Random Forest
DDS	Data Distribution Service	RMS	Reconfigurable Manufacturing System
DL	Deep Learning	RNN	Recurrent Neural Network
DNN	Deep Neural Network	RQ	Research Question
DQN	Deep Q Network	R&D	Research and Development
ELM	Extreme Learning Machine	SAE	Stacked Autoencoder
FEA	Finite Element Analysis	SARSA	State-action-reward-state-action
GBT	Gradient-Boosted Tree	SVM	Support Vector Machine
GMM	Gaussian mixture model	SVR	Support Vector Regression
GPR	Gaussian Process Regression	SWRL	Semantic Web Rule Language
GRNN	Generalized Regression Neural Network	USD	United States Dollar
HMD	Head Mounted Display	VR	Virtual Reality
HMI	Human-Machine Interface	WoS	Web of Science
HMM	Hidden Markov model	XML	Extensible Markup Language

1. Introduction

Machine tools, also known as the “mother machines” that “help people to make things” (“Mother Machines, MIT Technology Review” 2021), have always been playing a pivotal role in the manufacturing world since their performance significantly affects the product quality and production efficiency of manufacturing systems. Nowadays, machine tools are widely employed in a variety of industries including automotive, aerospace & defense, general machinery, precision engineering, power & energy, construction equipment, among others. Based on a market analysis report ("Machine Tools Market Size, Share & Research Report" 2021), the global machine tools market size was valued at USD 112.78 billion in 2019 and is projected to reach USD 151.90 billion by 2027. It is obvious that the advancement of machine tool technologies has a profound impact on the global economy.

In the last decade, rapid advancements in ICT have triggered the fourth industrial revolution, i.e., Industry 4.0. While the previous three industrial revolutions are characterized by water and steam powered mechanical production (Industry 1.0), electrical energy powered mass production (Industry 2.0), and computer and IT enabled automation (Industry 3.0), Industry 4.0 is expected to dramatically transform current manufacturing systems into CPPS based on various emerging technologies such as CPS, IoT, IoS, cloud/fog/edge computing, AI, and big data analytics (Henning, Wolfgang, and Johannes 2013). In the era of Industry 4.0, modular structured smart factories will be established, in which CPPS monitor physical processes, create digital twins of the physical world, and make decentralized decisions (Monostori 2014). IoT enables CPPS to communicate and cooperate with each other and humans in real time. IoS allows various types of services to be offered and utilized by participants across the value chain (Hermann, Pentek, and Otto 2016). Manufacturing systems become more flexible, more intelligent, and more autonomous, thus enabling mass customization with improved product quality and production efficiency. Overall, digitalisation and servitisation of manufacturing systems can be summarized as one of the ultimate goals of Industry 4.0 (Coreynen, Matthyssens, and Van Bockhaven 2017; Kohtamäki et al. 2020). From the technological perspective, digitalisation represents great data availability, accessibility, interoperability, connectivity, and efficient data communication, computation, and storage. Meanwhile, servitisation represents integrated product-service solutions such as advanced data analytics and visualization, high-fidelity simulation and prediction, intelligent decision-making support and human-machine interaction, and various value-added manufacturing services.

As the core component of a manufacturing system, machine tools will no doubt play a crucial role in the era of Industry 4.0. Hence, digitalisation and servitisation of machine tools become a major requirement as well as a critical challenge. In fact, the technological evolution of machine tools has, to a large extent, mirrored the history of industrial revolutions. Xu (2017) summarized the technological evolution of machine tools as four stages: mechanically driven and manually controlled machine tools (Machine Tool 1.0); electrically driven and numerically controlled machine tools (Machine Tool 2.0); CNC machine tools (Machine Tool 3.0); and Cyber-Physical Machine Tools (Machine Tool 4.0). CPMT represent the next-generation machine tools that deeply integrate the machine tool and machining processes with computation and networking based on CPS technology (Liu and Xu 2017). Compared to current CNC machine tools, CPMT have a higher level of accessibility, connectivity, intelligence, adaptivity, and autonomy (Liu et al. 2018). Hence, CPMT is considered as a promising solution to the digitalisation and servitisation of next-generation machine tools that facilitates the development of CPPS and smart factories in the era of Industry 4.0.

Ever since the term "Industry 4.0" ("Industrie 4.0" in German) was coined from a project in the high-tech strategy of the German government in 2011, applications of Industry 4.0 technologies in manufacturing have attracted extensive attention in both academia and industry. Figure 1 shows the annual publication volume of research works that apply typical Industry 4.0 technologies in manufacturing from 2011 to 2020. The data was obtained from WoS Core Collection database, using 'TOPIC: ("manufacturing") *AND* TOPIC: ("name of technology")' as the search query for each of the Industry 4.0 technologies. In WoS, the search field 'TOPIC' covers title, abstract, and keywords of the publications. Eight names of technology (and their variants) were used for the search, including 'Industry 4.0', 'CPS', 'IoT/IIoT', 'AI/ML/DL', 'cloud/fog/edge computing', 'big data', 'AR/VR' and 'digital twin'. In addition, non-refereed publications such as conference proceedings, book chapters, and commentaries were excluded to derive quality publications. Results in Figure 1 show that most studies that apply Industry 4.0 technologies in manufacturing started between 2011 and 2014. Though the research on AI/ML/DL and cloud/fog/edge computing in manufacturing have a longer history, their annual publication volume had always been kept below 30 before 2011. From 2014 to 2016, all the topics maintained a steady and slow growth with similar publication volumes. From 2016 to 2020, all the topics have experienced a rapid increase, resulting in a significant number of publications on each topic.

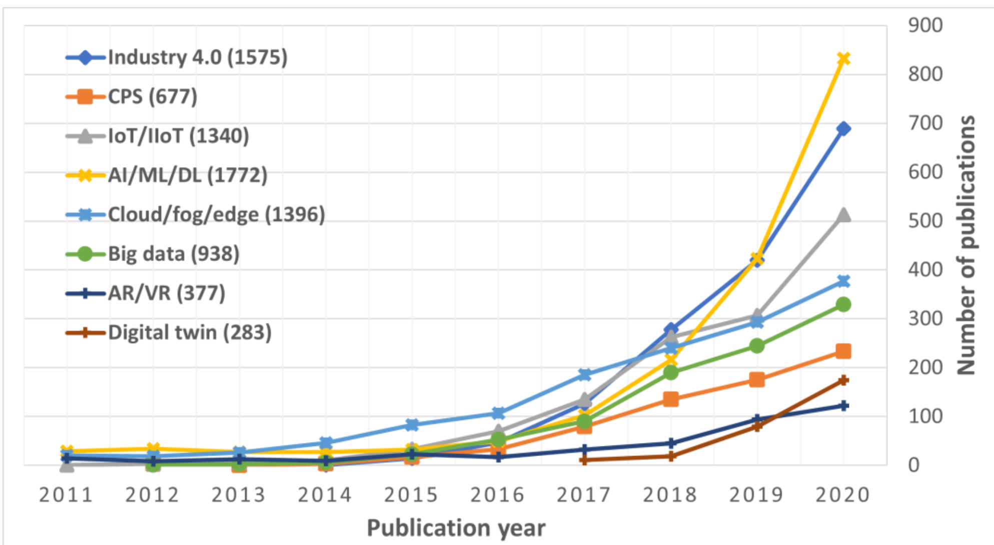

Figure 1. Annual publication volume of research applying typical Industry 4.0 technologies in manufacturing

The total number of publications of each topic is indicated along with the legend in Figure 1. It is obvious that huge amounts of research works on Industry 4.0 technologies in manufacturing have been conducted in the last decade. Meanwhile, a considerable amount of surveys and review articles on Industry 4.0 (Zheng et al. 2021; Liao et al. 2017; Lu 2017), smart manufacturing (Zhong et al. 2017; Mittal et al. 2018; B. Wang et al. 2020), smart factory (Strozzi et al. 2017; Osterrieder, Budde, and Friedli 2020), and other related topics have also been reported.

However, there have been few review articles on the development of machine tools in the era of Industry 4.0, despite that a considerable amount of research works that apply Industry 4.0 technologies in machine tools to improve their digitalisation and servitisation have been conducted.

Consequently, the following four Research Questions with respect to the development of machine tools in the era of Industry 4.0 remain unanswered:

RQ1: What are the trends and focuses of research on machine tools in the last decade?
RQ2: What is the current status of research on digitalisation and servitisation of machine tools?
RQ3: How can the emerging Industry 4.0 technologies be used to develop the next-generation machine tools towards digitalisation and servitisation?
RQ4: What are the major research issues and challenges of the digitalisation and servitisation of next-generation machine tools?

This paper attempts to answer these RQs by reviewing research related to digitalisation and servitisation of machine tools in the last decade and proposing a conceptual framework of the next-generation CPMT. The structure of this paper is shown in Figure 2. The following four sections aim to answer the four RQs, respectively. Section 2 provides a bibliometric analysis of research on machine tools in the last decade to investigate the research trends and focuses. A qualitative literature review is presented in Section 3 to analyze the current status of research on digitalisation and servitisation of machine tools. In Section 4, we propose a conceptual framework of CPMT to illustrate how Industry 4.0 technologies can be utilized to achieve digitalisation and servitisation of next-generation machine tools. The major research issues and challenges are identified and discussed in Section 5. Finally, Section 6 concludes the paper with final remarks.

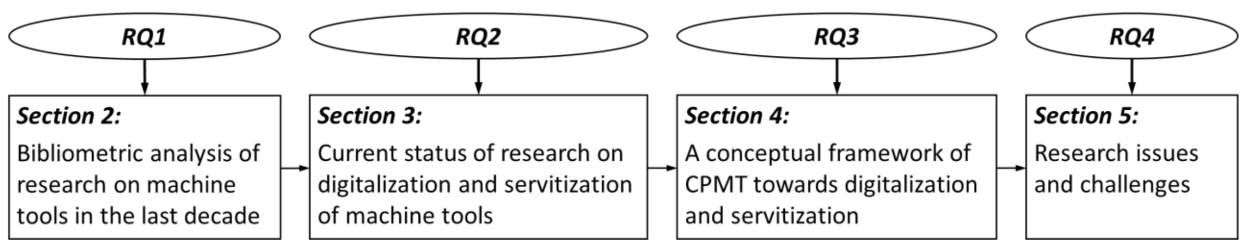

Figure 2. Research Questions and the structure of this paper.

2. Bibliometric analysis of research on machine tools in the last decade

In general, research on machine tools covers a wide range of research topics, resulting in a huge number of publications with distinctively different research focuses over the past several decades. To investigate the research trends and focuses of machine tools in the last decade, this section provides a bibliometric analysis using the data gathered from the WoS Core Collection database. To include the commonly used variant forms of the term 'machine tool' such as 'machine tool(s)', 'machine-tool(s)', and 'machining tool(s)', we used 'TOPIC: ("machin* tool*")' as the search query to collect the bibliometric data of all machine tools-related publications. Again, to derive quality publications among different types of documents in the WoS database, only journal articles and reviews are included for the bibliometric analysis.

2.1 Annual publication volume

Publication volume is an important factor that indicates the amount of research interest and effort paid by researchers in a specific area. Figure 3 shows the annual publication volume of research on machine tools from 1991 to 2020 in the WoS database. It can be seen that from 1991 to 2010, the annual publication volume had slowly climbed from 88 to 244 with some small fluctuations. In 2011, the year when the term ‘Industry 4.0’ was first coined, a slight rise brought the number to 293. From 2011 to 2014, the very beginning of Industry 4.0, the number steadily increased to 345. In 2015, the number suddenly jumped to 485 with a 40.6% increase. Then from 2015 to 2020, the annual publication volume kept a rapid and steady increase with approximate 10% annual growth and reached 821 in 2020.

In the last decade (from 2011 to 2020), the total number of machine tools-related publications is 5,115, averaging at 511 per year. The large number of publications indicates that enormous amounts of research effort have been increasingly devoted to machine tools in the last decade, which also demonstrates the crucial role that machine tools have been playing in the manufacturing world. Based on the growing tendency shown in Figure 3, it can be predicted that the annual publication volume of research on machine tools will keep increasing in the coming years with the average number of publications above 850 per year. Therefore, it is necessary to analyze the current trends and focuses of research on machine tools and discuss the future research directions of next-generation machine tools in the era of Industry 4.0.

Figure 3. Annual publication volume of research on machine tools from 1991 to 2020.

2.2 Country/region and organization

Research on machine tools have been extensively studies all over the world. The bibliometric data from 2011 to 2020 indicates that 20 countries/regions have contributed more than 50 publications on machine tools in the last decade. Figure 4(a) shows the detailed distribution of the 5,115 publications on machine tools from 2011 to 2020 based on their country/region. China has dominated the research on machine tools in the last decade with the highest publication volume (43.1%). United States ranked at the second place with 7.5%. These two leading countries contributed nearly half of the total publication volume. The other leading countries/regions include Germany (5.4%), Japan (5.2%), Taiwan (5.2%), England (4.9%), India (4.3%), and Canada (4.2%). Together, the top eight countries/regions have contributed about 80% of publications on machine tools in the last decade. Figure 4(b) shows the co-authorship network among the top 20 countries/regions created using the VOSviewer software. The size of the nodes indicates the publication volume of the country/region, while the thickness of the links represents the co-authorship frequency between two countries/regions. As shown in Figure 4(b), the strongest collaborations are the ones between China and United States, and China and England. Frequent collaborations are also observed between China and Canada, China and Japan, United States and Japan, and United States and Germany.

The top 20 organizations publishing works on machine tools in the last decade are listed in Figure 5. 16 out of the 20 organizations are universities in China. Huazhong University of Science and Technology and Xi An Jiaotong University are the top two leading organizations. Together, these two organizations contributed 7% of the total publication volume. Other leading organizations, including Harbin Institute of Technology, Shanghai Jiao Tong University, Chongqing University, Zhejiang University, and Tsinghua University, have all contributed more than 100 publications on machine tools in the last decade.

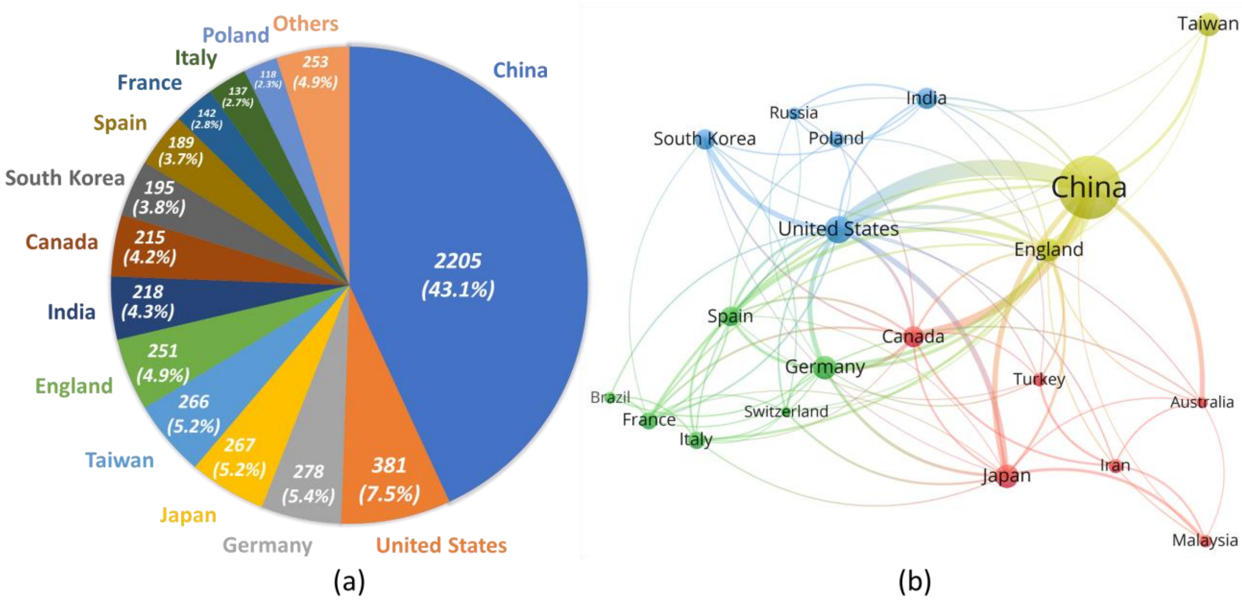

Figure 4. (a) Distribution of publications on machine tools by country/region from 2011 to 2020; (b) Co-authorship network among the top 20 countries/regions.

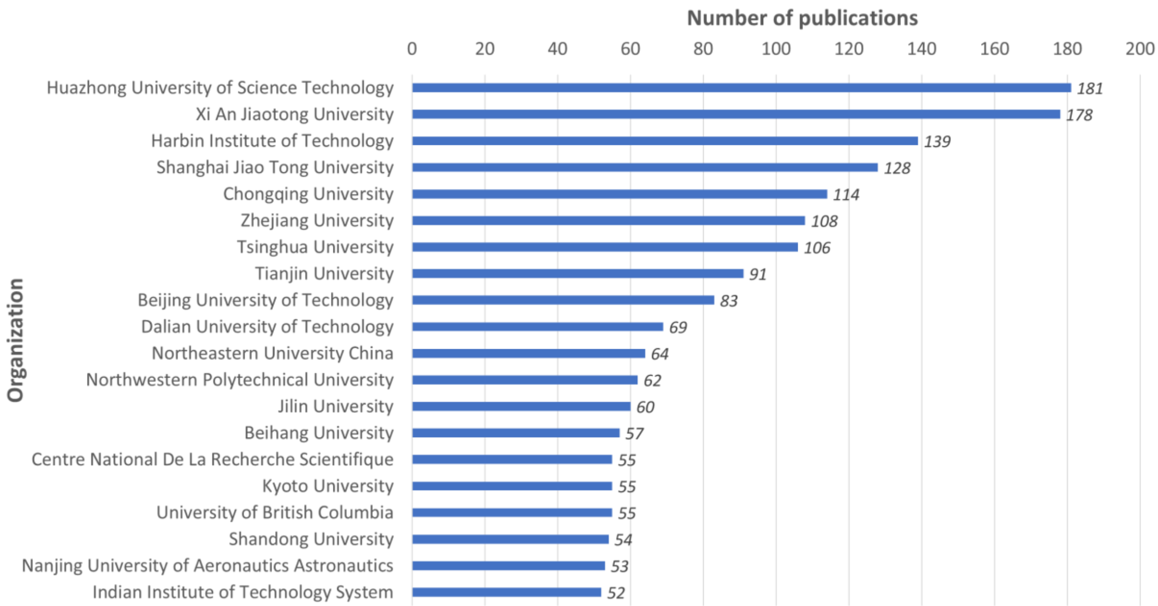

Figure 5. Top 20 organizations publishing works on machine tools from 2011 to 2020.

2.3 Top journal sources

The top 20 journals publishing works on machine tools based on the number of publications in the last decade are summarized in Figure 6. International Journal of Advanced Manufacturing Technology, ranking at the top, contributed 930 publications, which constitutes 18.2% of the total publication volume and is 4.6 times as the second journal, i.e. International Journal of Machine Tools and Manufacture. The other leading journals that contributed more than 100 publications include Precision Engineering, Proceedings of the Institution of Mechanical Engineers Part B: Journal of Engineering Manufacture, and CIRP Annals Manufacturing Technology.

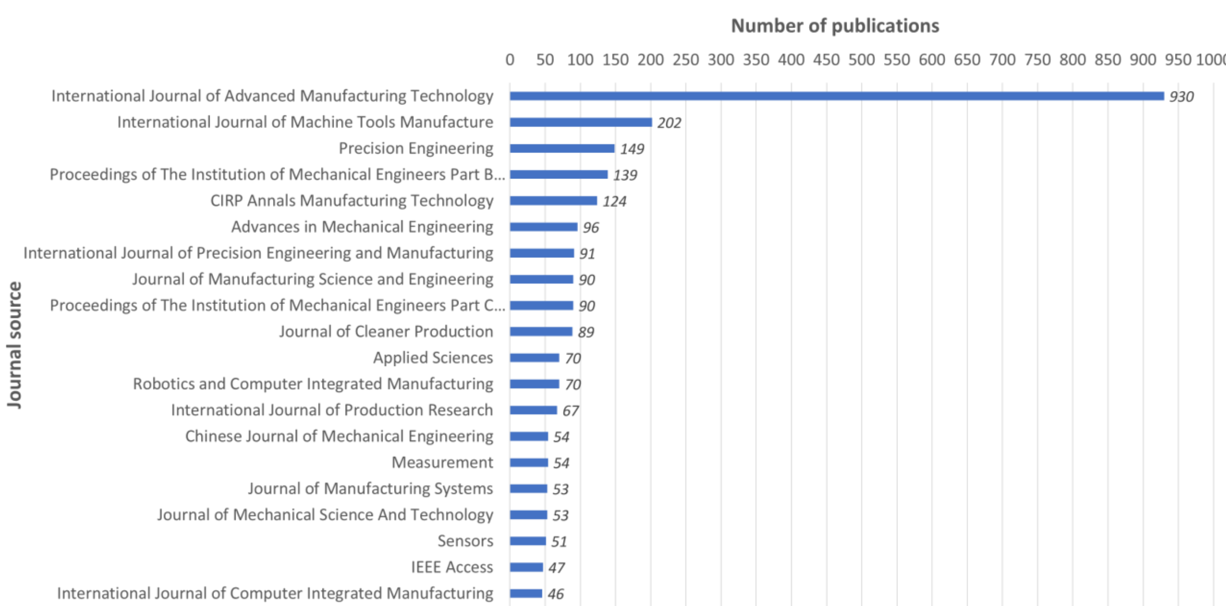

Figure 6. Top 20 journals publishing works on machine tools from 2011 to 2020.

2.4 Keywords co-occurrence analysis

To investigate the trends and focuses of research on machine tools in the last decade, a keywords co-occurrence analysis is conducted using VOSviewer, a software tool that is widely used for constructing and visualizing bibliometric networks. It is noted that the bibliometric data of the 5,115 publications collected from WoS database contains two types of keywords: 1) author keywords – keywords that are provided by the authors; and 2) Keywords Plus – algorithmically inferred words or phrases that do not appear in the title but are frequently used in similar articles. In this research, we used only the author keywords to analyze the research trends and focuses reflected by the researchers. In addition, data cleaning was also performed by aggregating variants of the same keywords and removing the meaningless keywords.

Table 1 lists the frequently used keywords (co-occurred 20 times or more) in the publications on machine tools from 2011 to 2020. It can be observed from Table 1 that research on machine tools covers a wide range of different topics. The most frequently used keywords such as compensation, optimization, thermal error, and geometric error indicate that improving machining accuracy has been the most studied research issue.

Table 1. Frequently used keywords in publications on machine tools from 2011 to 2020.

keyword	Count	keyword	Count	keyword	Count	keyword	Count
Machine tool	963	Energy consumption	70	On-machine measurement	37	Machine learning	25
Compensation	165	Energy efficiency	70	CAPP	36	Metrology	24
Machining	148	Turning	58	Contour error	35	Energy saving	23
Milling	121	Modelling	57	Laser tracker	35	Freeform surface	23
CNC	120	Simulation	55	Ball screw	34	High-speed machining	23
Optimization	120	Rotary axis	51	Error identification	33	Interpolation	23
Thermal error	118	Stability	51	Error modeling	33	Reliability	23
Geometric error	116	Genetic algorithm	48	Modal analysis	33	RMS	23
Chatter	112	Tool path	43	Double ball bar	32	STEP-NC	23
Spindle	110	Machining process	42	Kinematics	31	Ultra-precision machining	23
FEA	105	Measurement	42	Cutting tool	30	Dynamic characteristics	22
Surface roughness	104	Sustainable manufacturing	42	Grinding	29	Machining parameters	22
Tool wear	97	Volumetric error	42	Temperature	29	PSO	22
Vibration	94	Industry 4.0	41	Thermal deformation	29	Energy	21
Cutting force	85	Calibration	40	Uncertainty	29	Motion control	21
Dynamics	79	Feed drive	40	Control	28	Screw theory	21
5-axis machining	77	Sensitivity analysis	38	Damping	28	Taguchi method	21
Monitoring	73	Stiffness	38	Parallel mechanism	28	Manipulator	20
Accuracy	72	Neural networks	37	Friction	26	Tool condition monitoring	20

To better understand the research focuses represented by the various keywords, we grouped the keywords listed in Table 1 into nine categories and ranked the keywords in each category based on their occurrences in the publications (Figure 7). Modelling, simulation, compensation, and optimization are closely coupled topics that have been most frequently studied. Specific research focuses include the thermal error, geometric error, dynamics, and stability of machine tools. FEA has been extensively used as the modelling and simulation method. Process monitoring has been a hot topic of machine tool research. Chatter, vibration, and cutting force are the most frequently monitored objectives. Process planning and control has also been a research focus that covers topics such as CNC, tool path, and CAPP. Measurement and calibration have been widely studied. Surface roughness and tool wear are among the top measurands which are also frequently used as the targets for prediction. Energy efficiency of machine tools has also been a hot topic in the last decade in association with the sustainable manufacturing concept. The most studied types of machining process include milling, 5-axis machining, and turning. Spindle has been the most studied machine tool component, followed by rotary axis, feed drive, ball screw, and cutting tool. Data analytics methods that have been frequently used include genetic algorithm, sensitivity analysis, and neural networks. The manufacturing paradigms that have been frequently discussed with machine tools include sustainable manufacturing, Industry 4.0, and RMS.

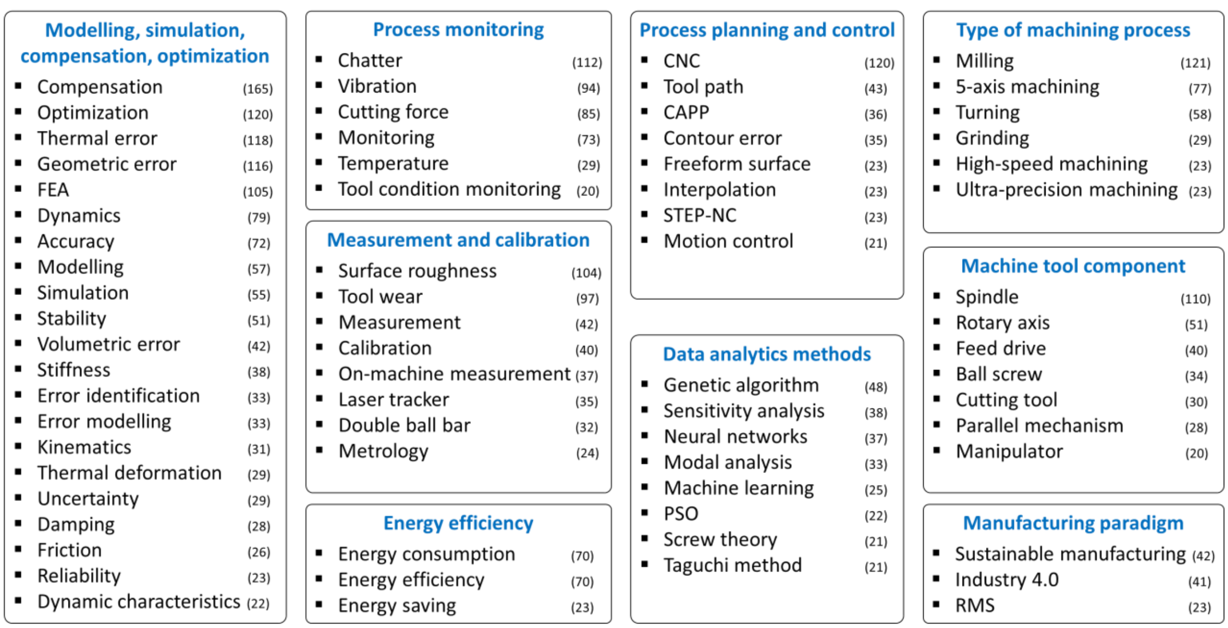

Figure 7. Categorization of frequently used keywords.

To investigate the research trends of machine tools in the last decade, a temporal keywords co-occurrence network is created based on the bibliometric data as shown in Figure 8. Only the keywords co-occurred more than 20 times are included to ensure the clarity of the network. The color gradient from blue to yellow represents the average publication year of the keywords from 2011 to 2020. The size of the node indicates the number of occurrences of the keyword, while the thickness of the link between two nodes indicates their co-occurrence frequency. The subtle difference in the color of nodes indicates that most research topics of machine tools did not show a clear changing trend in the last decade. However, it is obvious that Industry 4.0 and machine learning have attracted a rapidly increasing attention in the field of machine tools in recent years. As discussed previously, Industry 4.0 aims at digitalisation and servitisation of manufacturing systems. On the other hand, machine learning is used to improve the intelligence of machine tools, which eventually also contributes to servitisation. Therefore, it can be concluded that digitalisation and servitisation are becoming a new research trend of machine tools.

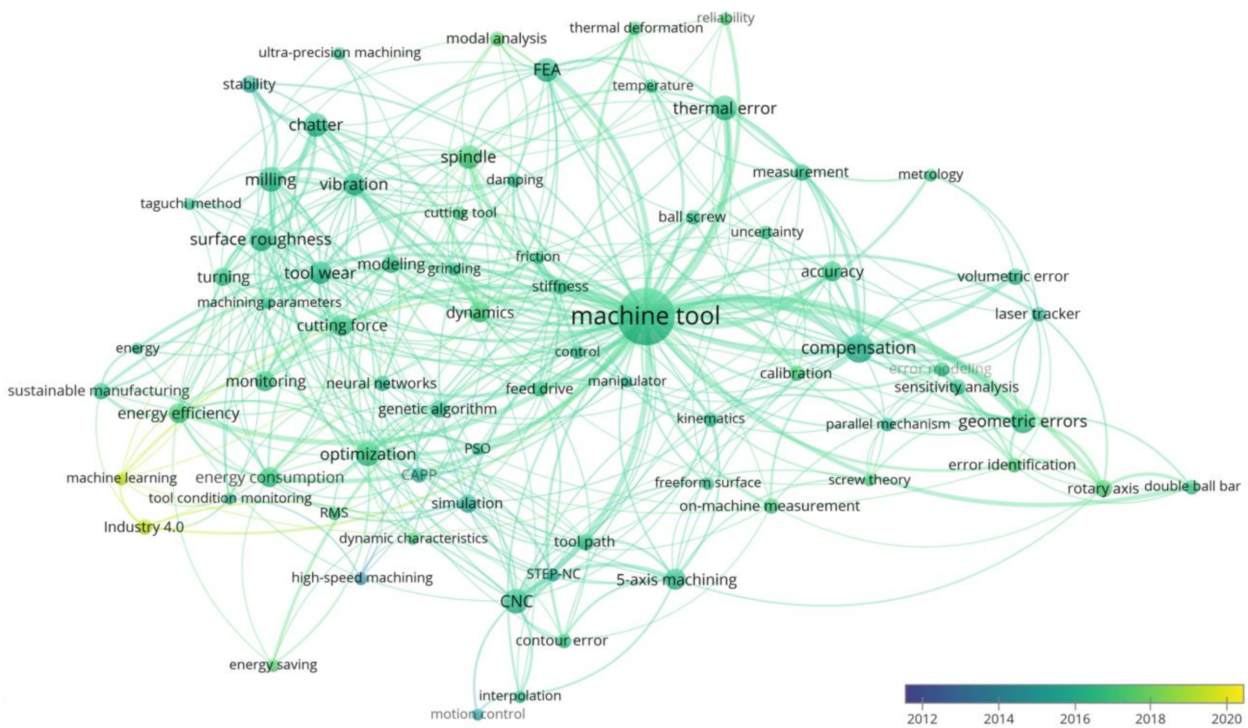

Figure 8. Overlay visualization of keywords co-occurrence network.

3. Current status of research on digitalisation and servitisation of machine tools

The bibliometric analysis presented in the previous section shows that digitalisation and servitisation of machine tools are becoming a new research trend in the era of Industry 4.0. In this section, we provide a qualitative literature review to analyze the current status of research on digitalisation and servitisation of machine tools. An overview of research works that apply Industry 4.0 technologies in machine tools is provided first. Then the specific technologies, methods, standards, architectures, and applications related to digitalisation and servitisation of machine tools are reviewed and discussed in detail.

3.1 Overview of Industry 4.0 technologies applied in machine tools

Figure 9 shows the annual publication volume of research works that apply typical Industry 4.0 technologies in machine tools from 2011 to 2020. Similar to the search performed in Section 1, we used 'TOPIC: ("machin* tool*") AND TOPIC: ("name of technology")' as the search query to collect the publication data from the WoS Core Collection database. Again, only journal articles were included to derive quality publications. The total number of publications on each topic is indicated along with the legend in Figure 9. Compared to the results shown in Figure 1, it is surprising that, despite the vital role machine tools play in manufacturing, the amount of research works applying Industry 4.0 technologies in machine tools only constitutes about 5% of those applying Industry 4.0 technologies in manufacturing. This indicates that Industry 4.0 technologies have not attracted much attention in the field of machine tools in the last decade. However, on the other hand, similar upward trends have shown in most of the topics since 2016. AI/ML/DL, Industry 4.0, and digital twin have been the fastest growing ones; CPS, IoT/IIoT, cloud/edge/fog computing, and big data experienced some fluctuations during the increase; while AR/VR stayed inactive with annual publication volume always below 5. Overall, research on applying typical Industry 4.0 technologies in machine tools is at an early yet fast-growing stage. Nevertheless, a considerable amount of research on digitalisation and servitisation of machine tools has already been conducted in the last decade. The remainder of this section presents a qualitative review of the related research works.

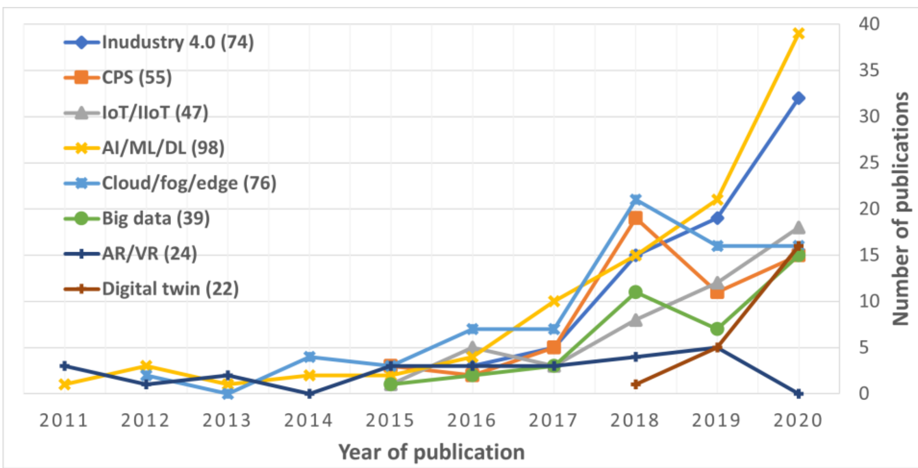

Figure 9. Annual publication volume of research works applying typical Industry 4.0 technologies in machine tools

3.2 Digitalisation of machine tools

From the technological perspective, digitalisation of machine tools represents great data availability, accessibility, interoperability, connectivity, and efficient data communication, computation, and storage. This subsection reviews recent research works on the key enabling technologies for the digitalisation of machine tools, including 1) data acquisition techniques, 2) data communication protocols, 3) information modelling methods, and 4) digital twin.

3.2.1 Data acquisition techniques

Data acquisition is the most fundamental requirement for the digitalisation of machine tools since it determines the data availability and accessibility of a machine tool. In general, machine tool data can be divided in two categories: 1) internal data, and 2) external data. Internal data are provided by the machine tool's internal sensors, PLC, and CNC system. These data represent the machine tool's internal state such as power status, operation mode, program information, axis positions and speeds, spindle speed, system messages, and alarms. The availability and accessibility of the internal data highly depend on the machine tool manufacturers. Unfortunately, machine tool manufacturers usually consider the internal data as confidential information. Most commercial CNC machine tools are proprietary systems that only display some of the internal data locally. Though there exist some open CNC software such as LinuxCNC, they are rarely used in real-world production systems due to their limited functions. Hence, data acquisition of machine tools' internal data is a difficult task. However, it is noted that in recent years, machine tool manufacturers are trying to make some of the internal data available for their customers by supporting some standardized communication protocols. Recent works on the data communication protocols for machine tools will be discussed in the next subsection. External data refer to the process monitoring data collected by external sensors. Machining process monitoring has been extensively studied in the past decades. The common measurands and their corresponding sensing techniques have been comprehensively summarized in several review articles (Teti et al. 2010; Nee 2015; Lauro et al. 2014).

Figure 10 shows the schematic diagram of the typical machine tool components and the common measurands. The commonly used sensors for the measurands and some example research works are listed in Table 2. These sensors have also been frequently combined as multi-sensor data acquisition systems to achieve various monitoring and prediction tasks such as machine tool health monitoring (Caggiano 2018; Cheng et al. 2019), machining condition recognition (Liu et al. 2018), energy consumption monitoring (Hu et al. 2012), tool wear prediction (Wu et al. 2018; Rizal et al. 2017), and so forth.

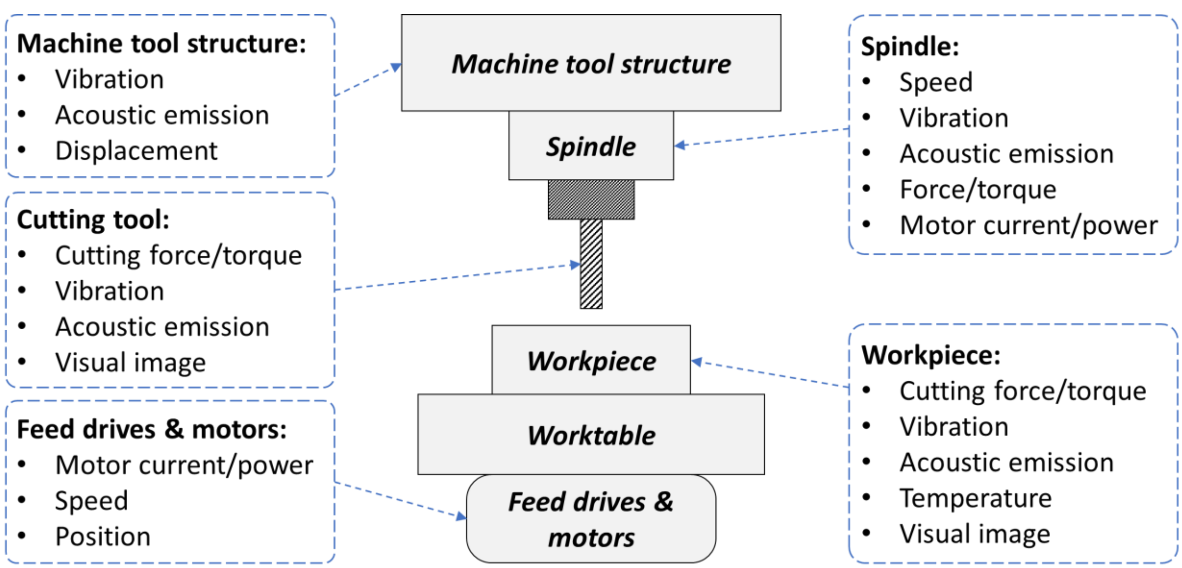

Figure 10. Schematic diagram of machine tool components and common measurands.

Table 2. Commonly used sensors for machine tools.

Measurands	Commonly used sensors	Example research works
Motor current/power	Hall effect current sensor, magnetic current sensor, power meter	(Liu et al. 2020; Nguyen, Ro, and Park 2019)
Position/speed	Linear encoder, proximity sensor, rotary displacement sensor, laser tracker	(Bourogaoui, Sethom, and Belkhodja 2016; Wang and Maropolous 2013)
Cutting force/torque	Strain gauge, piezoelectric force transducer, piezoelectric torque sensor, dynamometer	(Polvorosa et al. 2017; Grossi et al. 2015)
Vibration	Accelerometer, piezoelectric transducer, laser doppler vibrometer	(Bhuiyan and Choudhury 2015; Rao, Murthy, and Rao 2014)
AE	Piezoelectric AE sensor	(Bhuiyan et al. 2016; Duro et al. 2016)
Temperature	Thermocouple, resistance thermometer, radiation pyrometer, infrared thermometer	(Abdulshahed et al. 2015; Abdulshahed et al. 2016)
Visual image	CCD sensor, CMOS sensor	(Tootooni et al. 2016; Molnar et al. 2019)

3.2.2 Data communication protocols

With huge amounts and various types of field-level data being collected from machine tools and sensors, efficient data communication becomes a crucial requirement for the digitalisation of machine tools. Open-source, cross-platform, and standardized data communication protocols for machine tools are the key to this requirement since they determine the machine tools' data accessibility, connectivity, interoperability, and communication efficiency. The rapid advancement of IoT and IIoT technologies in recent years has triggered the introduction of various standardized data communication protocols such as MQTT, CoAP, AMQP, and DDS (Figueroa-Lorenzo, Añorga, and Arrizabalaga 2020). Their implementation in the envisioned IIoT, CPPS, and smart factory has also been discussed (Ding et al. 2019; Wu, Meng, and Gray 2017). However, as mentioned previously, most commercial CNC machine tools do not support these communication protocols due to their proprietary nature. In this context, a collective effort from both researchers and machine tool manufacturers has been devoted to improving the data accessibility and connectivity of CNC machine tools. As a result, two standardized communication protocols that allow data communication between machine tools and other systems have been developed, i.e. MTConnect and OPC UA.

MTConnect ("MTConnect" 2021), first released by the MTConnect Institute in 2008, is an open, royalty-free, and standardized communication protocol that allows data exchange between manufacturing equipment and software applications. It offers a semantic vocabulary for manufacturing equipment to provide structured, contextualized data with no proprietary format. MTConnect is developed specifically for CNC machine tools, and hence attracted significant attention from the machine tool manufacturers. Currently, more than 20 machine tool brands (Fanuc, Siemens, Mazak, DMG Mori, Okuma, Haas, etc.) offer MTConnect support from the factory or via third-party developers.

OPC UA (OPC Foundation 2019), first released by the OPC Foundation in 2008, is an open, platform-independent, and standardized communication protocol for industrial automation. OPC

UA can be used for a variety of industrial automation devices including CNCs, PLCs, robots, AGVs, sensor, actuators, and so forth. Since it is not specifically designed for machine tools, only a few machine tool brands (e.g. Siemens and DMG Mori) provide off-the-shelf OPC UA support. Nevertheless, the OPC Foundation and the German Machine Tool Builders' Association are jointly developing an OPC UA companion specification for CNC systems to broaden its support for machine tools.

While both MTConnect and OPC UA allow interoperable data exchange between machine tools and other systems or software applications, they differ from each other in many aspects. The comparisons between MTConnect and OPC UA are summarized in Table 3. Furthermore, it is worth mentioning that an MTConnect-OPC UA companion specification has also been jointly developed to ensure the interoperability and consistency between the two protocols.

Table 3. Comparisons between MTConnect and OPC UA.

	MTConnect	OPC UA
Scope of application	CNC machine tools and auxiliary systems.	Industrial automation devices including CNC machine tools, PLCs, robots, AGVs, sensor, actuators, etc.
Communication architecture	Adapter → Agent → Client One way, read only.	Server ↔ Client Bidirectional, read and write.
Underlying transport protocols	TCP/IP, HTTP	TCP/IP, HTTP
Message encoding	MTConnect XML	UA Binary and UA XML
Semantics	Predefined semantic vocabulary for CNC machine tools and auxiliary systems.	No semantic vocabulary.
Extensibility of semantic vocabulary	Relatively low. Extension needs to be achieved by modifying the data schemas defined by MTConnect.	N/A. Users need to define the semantic vocabulary.
Scalability	Relatively low.	High. Can be implemented in embedded devices.
Security	Low security. No special security policy implemented since it is read only.	High security. Authentication, authorization, encryption, and data integrity are integrated in authentication layer and transport layer.
Types of application	Monitoring.	Monitoring, control, M2M communication.
Support for machine tools	High. More than 20 machine tool brands offer off-the-shelf support. Third-party support is also available.	Low. Only a few machine tool brands provide off-the-shelf support.

The implementation of MTConnect and OPC UA in machine tools can significantly improve the data connectivity and interoperability, and hence enable various types of manufacturing services such as data analytics and visualization, remote process monitoring, control optimization, and shop floor management. Table 4 lists the representative research works that apply MTConnect and OPC UA in machine tools. For each research, the type of CNC system, the data communicated over the protocols, the network environment of case studies, and the objectives of applying the protocols are summarized.

Table 4. Research works applying MTConnect and OPC UA in machine tools.

Protocol	Reference	Type of CNC system	Data communicated via protocol	Network environment	Objectives
MTConnect	(Tong et al. 2020)	Self-developed open CNC	CNC data + multi-sensor data	Local network	To build a digital twin of machine tool for process monitoring, data visualization, and tool path analysis.
	(Guo, Sun, and Wu 2020)	Fanuc CNC	CNC data	Local network	To develop machine tool status monitoring functions.
	(Liu et al. 2018)	LinuxCNC	CNC data + multi-sensor data	Local network	To enable interoperable data communication and develop a CPMT with data analytics and process monitoring applications.
	(Coronado et al. 2018)	Okuma Multus	CNC data	Cloud-based	To correlate CNC data with data from MES, and develop a mobile MES app that allows tracking of product, cutting tools, operator activity, and power consumption.
	(Shin et al. 2018; Shin et al. 2016)	Machining simulator	CNC data (simulated)	Simulated environment	To combine historical CNC data with STEP-NC program information for generating predictive power consumption models.
	(José Álvares, Oliveira, and Ferreira 2018)	Fanuc CNC	CNC data	Cloud-based	To develop an Internet-based client-server model for monitoring and teleoperation of CNC machine tools.
	(Sunny, Liu, and Shahriar 2018; Liu et al. 2017)	Inventables X-Carve CNC	CNC data	Cloud-based	To enable Internet-based communication and remote monitoring of multiple geographically distributed machines in a cyber-physical manufacturing cloud.
	(Shin, Woo, and Rachuri 2017)	Fanuc CNC	CNC data + machine tool power data from power meter	Local network	To develop energy prediction models using historical machine-monitoring data and perform online optimization of cutting parameters.
	(Ridwan and Xu 2013)	LinuxCNC	CNC data + multi-sensor data	Local network	To integrate MTConnect-based process monitoring data STEP-NC-based process planning data and perform in-process feed-rate optimization.
OPC UA	(Mourtzis, Milas, and Vlachou 2018)	Proto Trak SMX	CNC data + multi-sensor data	Cloud-based	To develop an IoT-based production monitoring system for shop floor control using OPC UA.
	(Steffan et al. 2017)	Siemens SINUMERIK	CNC data + multi-sensor data	Local network	To optimize the process control of a grinding machine tool based on CNC and sensor data. OPC UA is used to allow communication between PID controller and CNC system.
	(Shin 2021)	Virtual simulator	CNC data + machining power (simulated)	Simulated environment	To develop an OPC UA-compliant cross-domain interface for exchanging data analytics models developed for manufacturing systems.
MTConnect + OPC UA	(Liu et al. 2019)	FANUC CNC + LinuxCNC	CNC data + multi-sensor data	Cloud-based	To enable interoperable data communication in a CPMT platform.

3.2.3 Information modelling methods

Information modelling is a key enabling technology for the digitalisation of machine tools. On the one hand, the complex machine tool data collected from various data sources need to be organized in a logical manner for efficient data analysis. On the other hand, the extensive machine tool knowledge such as property, capability, and functionality information need to be effectively managed so that they can be inferred, shared, and reused. Information model plays an important role for managing information and knowledge in manufacturing systems (Kjellberg et al. 2009). Furthermore, information model is also a prerequisite for developing the digital twins of manufacturing equipment (Lu et al. 2020). Based on different functional focuses, the information models for machine tools can be generally divided into two categories: 1) data-oriented information models that focus on the structure, terminology, definitions, and semantics of the machine tool data that need to be communicated and analyzed; and 2) knowledge-oriented information models that focus on the machine tool knowledge such as property, capability, functionality, and relationships between components. For data-oriented information models, MTConnect and OPC UA both provide their own information modelling methods since they are deeply integrated with the communication protocols and architectures. For knowledge-oriented information models, ontology-based and standard-based information modelling methods have been widely studied.

The MTConnect information model is specifically designed for machine tools. It is essentially a hierarchically structured XML file comprised of two primary types of XML elements: structural element and data entity. Structural elements represent the physical and logical components of a machine tool, while data entities represent the data collected from a machine tool. In addition, attributes can be added to the XML elements to provide additional descriptions. Figure 11(a) shows an example of the MTConnect information model for a CNC lathe.

OPC UA does not provide predefined information models with semantic information. Instead, it defines a generic and object-oriented information modelling method that provides a standard way for servers to represent objects to clients. An OPC UA information model contains nodes and references that represent objects, data, and their relationships. Developers need to model their complex systems as nodes and references in the OPC UA address space based on domain knowledge. Figure 11(b) shows an example of the OPC UA information model for a 3-axis milling machine.

Ontology is a technology that formally represents knowledge as a set of concepts within a domain (Lu et al. 2014). It has classes that represent things in reality, properties that give details to classes, and restrictions that create rules for the ontology (Järvenpää et al. 2019). OWL is the most used semantic web language for developing ontology models. SWRL and SPARQL query language are frequently used for generating rules and querying knowledge from the ontology models. In the field of manufacturing, ontology has been widely used for modelling various types of manufacturing resources and processes (Usman et al. 2013). For machine tools, some existing standards such as STEP (ISO 10303-238/242) and STEP-NC (ISO 14619-201) that are dedicated to describing machine tools and machining processes have also been used as references to develop information models for machine tools (Um, Suh, and Stroud 2016). Figure 11(c) and Figure 11(d) show two examples of ontology-based and STEP-NC-based machine tool information models, respectively. Knowledge-oriented machine tool information models contain rich knowledge about the property, capability, and functionality of machine tools and machining processes. Hence, they are commonly used to perform decision-making tasks such as machine tool selection, process planning, and fault diagnostics. Representative research works on knowledge-oriented machine tool information models are summarized in Table 5.

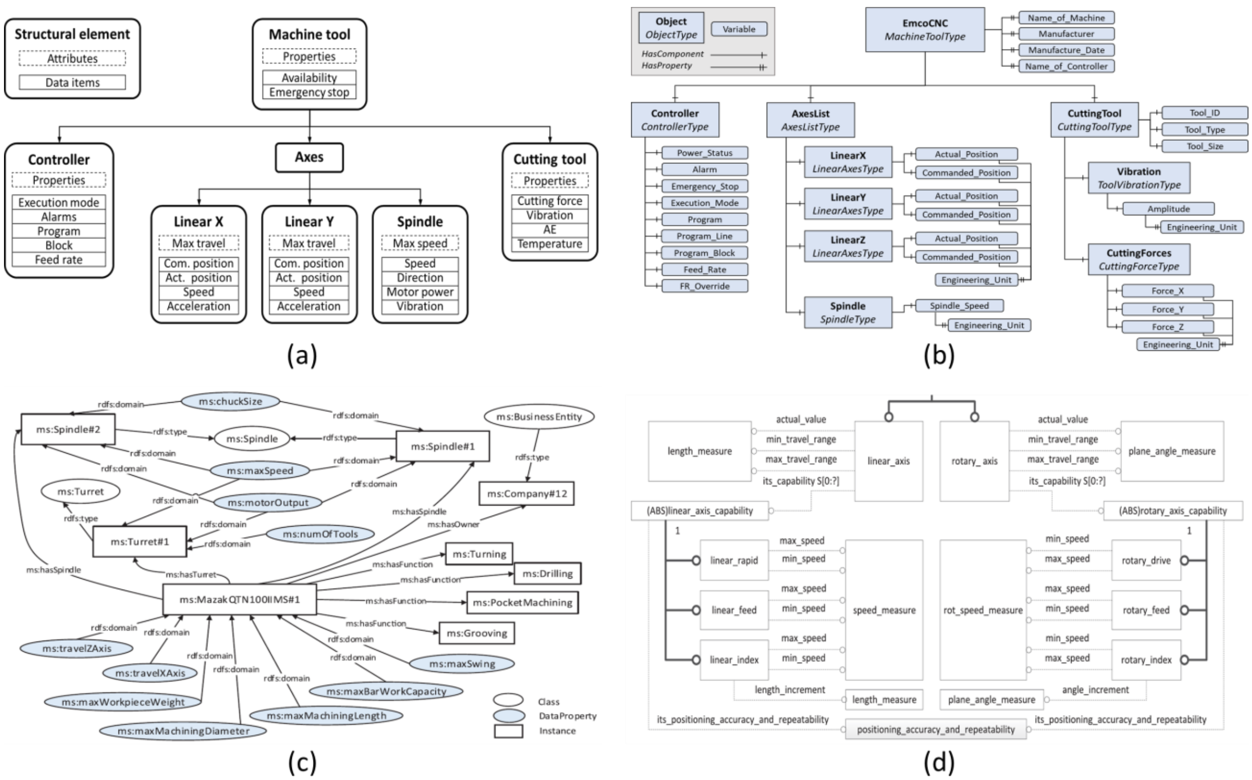

Figure 11. Examples of machine tool information model: (a) MTConnect information model (Liu et al. 2018); (b) OPC UA information model (Liu et al. 2019); (c) Ontology-based information model (Lu and Xu 2018); (d) STEP-NC-based information model (Vichare et al. 2015).

Table 5. Research works on knowledge-oriented machine tool information models.

Information modelling method	References	Standards used	Ontology development languages	Ontology development tools	Description
Ontology	(Zhao et al. 2021)	--	OWL	Protégé	Proposed an ontology-based method for constructing the digital twin of a CNC machine tool. The digital twin is used for cutting parameter optimization.
	(Xiang et al. 2018)	--	OWL	Protégé	Developed a manufacturing data integration and sharing method for machine tools and manufacturing services.
	(Zhou, Yan, and Xin 2017; Zhou et al. 2018)	--	OWL, SWRL, SPARQL	Protégé	Developed an ontology-based fault diagnosis method for machine tools.
	(Rehage and Gausemeier 2015)	--	OWL, SPARQL	Not mentioned	Developed an ontology-based machine tool selection method based on rough process descriptions.
	(Ramos et al. 2014)	--	OWL	Protégé	Developed a method that integrates ontology reuse with ontology validation and learning, thus improving the interoperability of the machine tool's ontology.
	(Nassehi and Newman 2012)	--	OWL	Java (for modelling the software blocks)	Proposed a method for representing machine tool elements as smart interlocking software blocks that are dynamically structured based on predefined ontology.
Ontology + standards	(Ming et al. 2020)	STEP	OWL, SWRL, SQWRL	Protégé	Develop an ontology-based module selection method for reconfigurable machine tools.
	(Lu and Xu 2018)	STEP-NC	OWL, Jena	Protégé, OntoSTEP plugin	Developed an ontology-based resource virtualization method for creating digital twins of machine tools.
	(Lu et al. 2014)	STEP, STEP-NC	OWL, SWRL	Protégé, OntoSTEP plugin	Developed an ontology-based information modelling method for manufacturing resources. The information model allows efficient resource virtualization and resource retrieval in cloud manufacturing systems.
Standards	(Vichare et al. 2018)	STEP, STEP-NC	--	--	Developed STEP/STEP-NC-based machine tool information models that represent the MCP of a machine tool, including its kinematic, static, and dynamic information.
	(Vichare et al. 2015)	STEP, STEP-NC	--	--	Developed a STEP-NC-based machine tool information model for representing machine tool health data based on capability profiles.

3.2.4 *Digital twin*

Digital twin is one of the fastest growing Industry 4.0 technologies in the past five years. In general, digital twin refers to an integrated multi-physics, multi-scale, probabilistic simulation of a complex product that uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding physical twin (Glaessgen and Stargel 2012). It represents an integrated solution to the digitalisation of manufacturing systems that combines various techniques including data acquisition and communication, modelling and simulation, and advanced data analytics (Tao et al. 2018). Recently, the concept, reference model, enabling technologies, applications, and business innovation perspectives of digital twin in manufacturing have been extensively discussed (Lu et al. 2020; Qi et al. 2019; Lim, Zheng, and Chen 2019). However, as mentioned in Section 3.1, research on digital twin for machine tools has not been widely investigated.

For machine tools, the function requirements for the digital twin mainly include (Liu et al. 2018): 1) representing both static properties and real-time status of the machine tool and machining processes; 2) monitoring and controlling the machine tool with built-in computation and intelligence; and 3) communicating with software applications and HMIs to provide intelligent decision-making support. Data acquisition, data communication, and information modelling, as discussed in the preceding subsections, are the fundamental requirements for developing the digital twin of a machine tool. Digital twin modelling methods can be generally categorized as three approaches: 1) data-driven approach, 2) model-driven approach, and 3) hybrid approach. Data-driven approach focuses on applying advanced data analytics methods on the machine tool data for data analysis, visualization, and decision-making tasks (Zhang et al. 2021). Model-driven approach focuses on the use of domain-specific simulation models such as dynamic models and FEA models to achieve high-fidelity process simulation, prediction, and optimization (Huynh and Altintas 2021). Hybrid approach combines both data- and model-driven approaches to achieve complex decision-making tasks such as model updating, predictive maintenance, and real-time control optimization (Luo et al. 2020).

Table 6 summarizes the existing research works on digital twin for machine tools, including the digital twin data, communication protocol, information model, digital twin modelling approach, software for digital twin application development, and application scenario of each work. It is noted that standardized communication protocols and information modelling methods have not been widely used for developing the digital twin. Data-driven approach has been most applied for modelling the digital twin. Machine tool status and process monitoring have been the most demonstrated digital twin applications. Nevertheless, there is still a lack of a systematic digital twin development method for machine tools.

Table 6. Research works on digital twin for machine tools.

Reference	Digital twin data	Communication protocol	Information model	Digital twin modelling approach	Software for digital twin application development	Application scenario
(Heo and Yoo 2021)	CNC data + tool vibration + spindle motor current	MTConnect/ OPC UA	--	Data-driven	Self-developed software framework named MDT4DE	Machining parameter optimization based on analysis of historical data stored in the digital twin.
(Huynh and Altintas 2021)	Machine tool property data + axes positions + structural vibrations	--	--	Model-driven	Self-developed C++ simulation environment using EasyDyn library	Simulation and prediction of the combined rigid body motion and vibrations of a 5-axis machine tool during machining operations.
(Zhang et al. 2021)	CNC data	MTConnect	MTConnect information model	Data-driven	Self-developed MTConnect client application	Real-time process monitoring and edge-computing enabled abnormality detection of machine tool data.
(Zhao et al. 2021)	CNC data + spindle power	--	Ontology-based information model containing process knowledge	Data-driven	Self-developed application	Cutting parameter optimization based on machining process knowledge and optimization algorithms in the digital twin.
(Wei et al. 2021)	Slider vibration signals	--	--	Hybrid approach (data-driven + FEA simulation)	Self-developed application	Model consistency retention of a machine tool digital twin based on vibration signal processing and FEA simulation.
(Jeon et al. 2020)	Machine tool property data + CNC data	OPC UA	OPC UA information model	Data-driven	Self-developed application	Machine tool status monitoring and remaining useful life prediction based on the machine tool status data in the digital twin.
(Tong et al. 2020)	CNC data + multi-sensor data	MTConnect	MTConnect information model	Data-driven	AnyCAD-based visual monitoring application + Android mobile monitoring app	Real-time process monitoring and tool path optimization based on data and analytics models in the machine tool digital twin.
(Wang et al. 2020)	CNC data	--	--	Hybrid approach (data-driven + multibody dynamic models)	Self-developed application	Estimation of multibody dynamic models of machine tool feed drive system using in-process CNC data in the machine tool digital twin.

(Wang, Lee, and Angelica 2020)	CNC data + vibration sensor data	Modbus TCP/IP	--	Data-driven	J-Mobile software	Cloud-based real-time machine tool condition monitoring based on digital twin data.
(Huang, Wang, and Yan 2020)	Machine tool structure, configuration, and kinematics	--	--	Model-driven	Self-developed application	Structure design, configuration generation, and configuration evaluation of reconfigurable machine tools based on digital twin.
(Luo et al. 2020)	CNC data + multi-sensor data	--	--	Hybrid approach (data-driven + multi-domain simulation model)	Self-developed application	Cutting tool life prediction based on a hybrid machine tool digital twin that contains process data and cutting simulation models.
(Liu et al. 2019)	CNC data + multi-sensor data	MTConnect + OPC UA	MTConnect information model + OPC UA information model	Data-driven	Self-developed OPC UA client application + AR-assisted HMI	Wearable AR-assisted HMI for real-time process monitoring and simulation of an interoperable CPMT platform based on the machine tool digital twins.
(Zhao et al. 2019)	CNC data	--	--	Data-driven	Self-developed application	Context-aware autonomous control optimization of a punching machine tool based on real-time digital twin data.
(Luo et al. 2019)	CNC data + multi-sensor data	OPC UA	OPC UA information model	Hybrid approach (data-driven + multi-physical simulation model)	MWorks software	Fault prediction and diagnosis of a milling machine based on process data and multi-physical simulation model in the machine tool digital twin.
(Liu et al. 2018)	CNC data + multi-sensor data	MTConnect	MTConnect information model	Data-driven	Self-developed MTConnect client application	Real-time machine tool status and process monitoring of a CPMT based on the machine tool digital twin.

3.3 Servitisation of machine tools

Broadly, machine tool-related services cover a wide range of research topics, including machine tool and machining process monitoring (Teti et al. 2010), machine tool PHM and predictive maintenance (Baur, Albertelli, and Monno 2020), machine tool selection (He et al. 2015), process planning (Xu, Wang, and Newman 2011), machining process simulation, prediction, and optimization (Kant and Sangwan 2014), and so forth. The specific methods and techniques of these services, which have already been extensively studied in the past decades, are not the focus of this paper. From the technological perspective, servitisation of machine tools represents integrated product-service solutions such as advanced data analytics and visualization, high-fidelity simulation and prediction, intelligent decision-making support and human-machine interaction, and various value-added manufacturing services. This subsection reviews recent research works on the key enabling technologies for the servitisation of machine tools, including 1) service-oriented system architectures, 2) advanced data analytics, and 3) intelligent human-machine interaction.

3.3.1 Service-oriented system architectures

Service-oriented system architecture is a critical requirement for the servitisation of machine tools. Traditional CNC machine tools are designed as isolated systems. The machine tool data are kept in the shop floor level, where only localized and limited manufacturing services can be provided. Based on the emerging cloud technologies such as cloud computing (Mell and Grance 2011), fog computing (Bonomi et al. 2012), and edge computing (Shi et al. 2016), service-oriented system architectures allow the field-level machine tool data to be shared with distributed computation resources through the Internet, and enable various types of manufacturing services to be efficiently generated, transmitted, and provided to the cloud, so that different users can access the services anywhere and anytime.

Service-oriented system architectures for manufacturing systems have been extensively discussed and studied in the last decade (Tao et al. 2014; Wu et al. 2015). The general goal of applying service-oriented system architecture for manufacturing systems is to provide distributed, fast-responding, on-demand, and quantifiable manufacturing services (Wang and Xu 2013). From the structural perspective, service-oriented system architectures can be categorized into two types based on the cloud technologies used, i.e. 1) cloud-based, and 2) fog/edge computing-based. In cloud-based manufacturing systems, field-level manufacturing data are directly uploaded to the cloud, where cloud computing resources (databases, servers, applications, etc.) are used to create different manufacturing services (Lu and Xu 2019). In fog/edge computing-based manufacturing systems, distributed high performance computing resources, data storage, and networking services are implemented on the fog/edge devices (between the data sources and the cloud), such that the computationally intensive data processing tasks can be performed at locations where large volumes of data are collected and stored (Wu et al. 2017). Compared to cloud-based architecture, fog/edge computing-based architecture can reduce the amount of data to be sent to the cloud, decrease network and Internet latency, and improve service response time (Liu et al. 2020).

Although various cloud/fog/edge computing-based manufacturing systems have been proposed, service-oriented system architectures that are specifically designed for machine tools have not been widely studied. Table 7 lists recent research works that apply service-oriented system architectures for machine tools. The type of system architecture, services provided, cloud computing platform and fog/edge devices used, and type of service application in each work are summarized. It can be seen that service-oriented system architectures allow various types of intelligent manufacturing services to be created and provided through the Internet. Cloud-based architectures can provide non-real-time services such as process monitoring, process planning, and machine tool selection; while fog/edge computing-based architectures enable real-time services such as anomaly detection, prognosis, and error compensation. Nevertheless, it is noted that most existing service-oriented system architectures only offer specific machine tool services, rather than providing a generic service mechanism that allows customizable services to be requested and generated.

Table 7. Research works that apply service-oriented system architecture for machine tools

Type of system architecture	Reference	Services provided	Cloud computing platform	Fog/edge device	Type of service application
Cloud-based	(Župerl and Čuš 2019)	Cloud-based on-line surface roughness monitoring.	Private cloud platform	--	Cloud software application
	(Zuperl and Cus 2019)	Cloud-based fixture condition monitoring based on simulation applications.	Private cloud platform	--	Cloud software application
	(Mourtzis et al. 2019)	Cloud-based process monitoring and tool path optimization.	Private cloud platform	--	Cloud software application
	(Terrazas, Ferry, and Ratchev 2019)	Cloud-based machine tool data analytics, data visualization, and energy consumption monitoring.	Amazon EC2	--	Cloud software application
	(Coronado et al. 2018)	Cloud-based machine tool status monitoring.	Private cloud platform	--	Web application
	(Caggiano 2018)	Cloud-based process monitoring and tool wear diagnosis.	Private cloud platform	--	Web application
	(Hung et al. 2017)	Cloud-based multi-user model creation for automatic virtual metrology using historical machine tool data.	Private cloud platform	--	Web application
	(Mourtzis, Vlachou, and Zogopoulos 2017)	Cloud-based machine tool status monitoring and AR remote maintenance.	Private cloud platform	--	Cloud software application and mobile AR application
	(Mourtzis et al. 2016)	Cloud-based dynamic process planning service based on real-time machine tool status from a process monitoring.	Private cloud platform	--	Web application
	(Chen et al. 2016)	Cloud-based machine tool and cutting tool selection based on machine tool knowledge.	Microsoft Windows Azure	--	Web application
	(Wang et al. 2014)	Cloud-based non-real-time thermal error compensation based on embedded CNC and PLCopen.	Private cloud platform	--	Cloud computing service
Fog/edge computing-based	(Zhou et al. 2018)	Fog computing-based real-time data processing and thermal error compensation.	Private cloud platform	Cortex-A8 ARM chip with embedded DSP unit	Software application
	(Wu et al. 2017)	Fog computing-based real-time process monitoring and data-driven prognosis.	GE Predix Platform	BeagleBone Black	GE Predix Machine software application
	(Zhang et al. 2021)	Edge-cloud computing-based real-time process monitoring and anomaly detection.	Private cloud platform	Self-developed microcontroller board	MTConnect client application
	(Lou et al. 2020)	Edge-cloud computing-based thermal error compensation.	Private cloud platform	Private edge computing platform	Software application

	(Liu et al. 2019)	Edge-cloud computing-based real-time process monitoring and surface roughness prediction.	Aliyun cloud platform	Computer	Cloud software application
	(Lin et al. 2019)	Edge computing-based real-time machine tool anomaly.	Private cloud platform	NVIDIA Jetson TX2	Software application
	(Županl and Čuš 2019)	Edge computing-based real-time surface roughness monitoring and cutting chip size control.	Private cloud platform	IoT gateway	Software application
	(Lo, Hu, and Chang 2018)	Edge computing-based real-time machine tool spindle temperature monitoring and prediction.	--	Self-developed microcontroller board	Software application

3.3.2 Advanced data analytics methods

Advanced data analytics is a key enabling technology for the servitisation of machine tools. In order to convert the huge amounts of raw machine tool data into meaningful information and provide various types of decision-making functions as intelligent services, advanced data analytics methods need to be applied. As mentioned in Section 3.2.1, machine tool data include not only the CNC data, but also different types of sensor signals. Hence, advanced data analytics methods for machine tools mainly include signal processing techniques and machine learning techniques.

Signal processing techniques have been extensively studied in the past decades and multiple review articles have been reported by Lauro et al. (2014), Nee (2015), Teti et al. (2010), and so forth. Figure 12 shows a generic signal processing scheme. The commonly used signal processing algorithms for signal pre-processing, feature generation, feature extraction, feature selection, etc. have been comprehensively summarized in the aforementioned references, and hence are omitted in this paper.

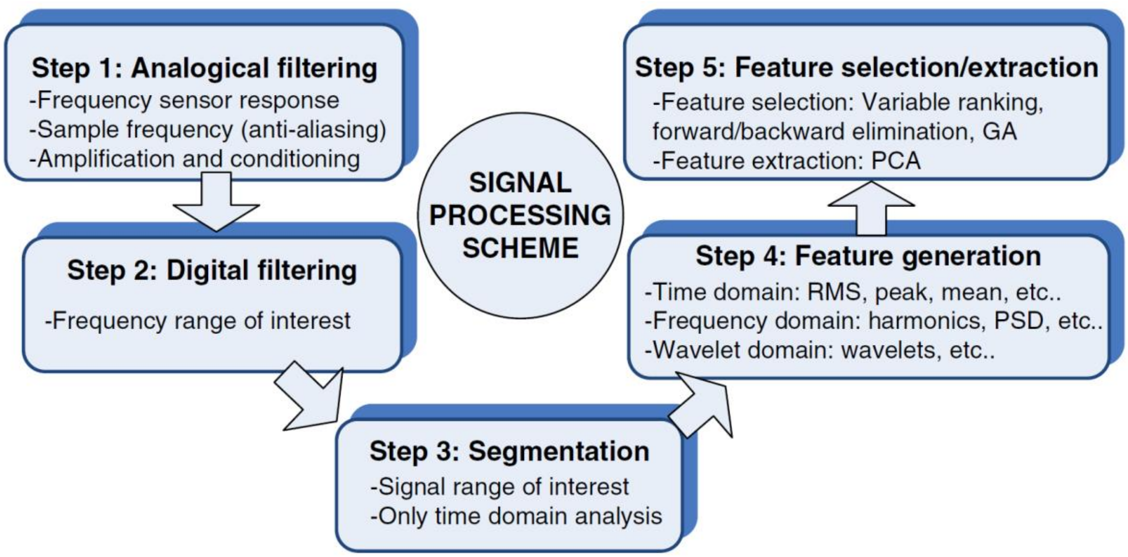

Figure 12. Generic signal processing scheme (Abellan-Nebot and Subirón 2010).

Currently, machine learning is one of the fastest growing research fields. A significant amount of different machine learning techniques has been developed to endow machines with intelligent decision-making capabilities without explicitly programming. Broadly, machine learning techniques can be categorized into three main types, including 1) supervised learning (linear regression, logistic regression, decision trees, RF, SVM, KNN, Naïve Bayes, ANN, CNN, RNN, etc.) that learns a function that maps an input to an output from labelled data, 2) unsupervised learning (K-means clustering, PCA, Apriori, Autoencoder, etc.) that learns patterns from unlabeled data, and 3) reinforcement learning (Q-learning, SARSA, DQN, DDPG, etc.) that optimizes behaviors based on reward gained through interaction with the environment. Furthermore, based on the three basic types, other machine learning methods such as semi-supervised learning (Van Engelen and Hoos 2020) and transfer learning (Pan and Yang 2010) have also been developed and widely studied.

As mentioned in Section 3.1, applications of machine learning techniques in machine tools have been proliferating in the last five years. Several review articles on machine learning techniques for process monitoring (Abellan-Nebot and Subirón 2010), tool condition monitoring (Mohanraj et al. 2020; Serin et al. 2020), and fault diagnosis (Lei et al. 2020; Schwendemann, Amjad, and Sikora 2021) have also been reported. The application of machine learning techniques in machine tools enables various intelligent decision-making functions that can be further integrated as intelligent services for machine tools.

Based on the types of the targeted services, Table 8 summarizes recent research works that apply machine learning techniques in machine tools, including the machine learning techniques applied and the input data for the machine learning techniques of each work. It can be seen that machine learning applications for tool condition monitoring/ prediction, thermal error modelling/ prediction/ compensation, machine tool prognostics/ anomaly detection, and energy consumption modelling/ prediction have attracted most attentions. Various types of machine tool data as mentioned in Section 3.2.1 have been used as the input for machine learning, including CNC data, various types of sensor data, and even images. Due to the high-accuracy, high-reliability, and high-robustness requirements, supervised machine learning techniques have been most applied in developing machine tool services. Unsupervised learning is usually combined with supervised learning to reduce the required data volume and training time (Grzenda and Bustillo 2019), and to address the overfitting and feature co-adaptation issues (Tian and Pan 2020). Transfer learning has also been applied to take advantage of existing knowledge and models (Mamledesai, Soriano, and Ahmad 2020; Kim, Shin, and Cho 2021). Reinforcement learning, however, has been rarely applied for developing machine tool services. Overall, existing research works indicate that the application of machine learning techniques plays a critical role for the servitisation of machine tools.

Table 8. Recent research works applying machine learning techniques in machine tools

Services	References	Machine learning techniques	Input data for machine learning
Tool condition monitoring/ prediction	(Zhang, Zeng, and Starly 2021)	LSTM	Cutting vibration
	(Zeng, Liu, and Liu 2021)	Deep CNN (ResNet-CBAM)	Cutting force + cutting vibration + AE
	(Chang, Wu, and Hsu 2020)	ANN	Cutting speed, feed rate, material removal volume
	(Nguyen, Nguyen, and Pham 2020)	SAE	Spindle vibration
	(Patange and Jegadeeshwaran 2020)	Decision tree + Bayes network + Naïve Bayes	Spindle vibration
	(Huang et al. 2020)	Bidirectional LSTM	Cutting force + tool vibration
	(Mamledesai, Soriano, and Ahmad 2020; Wu et al. 2019)	CNN	Tool wear images
	(Wang et al. 2019)	CNN + RNN (hybrid neural network)	Spindle power + tool wear images + machine surface images
	(García-Ordás et al. 2018)	SVM + computer vision	Tool wear images
	(Terrazas et al. 2018)	CNN	Cutting force
	(Ferguson et al. 2018)	GPR	Cutting vibration + AE

	(Wu et al. 2017)	ANN, SVR, RF (comparative study)	Cutting force + cutting vibration + AE
	(Madhusudana et al. 2016)	Naïve Bayes + Decision Tree	Cutting vibration
Thermal error modelling/ prediction/ compensation	(Liu et al. 2021)	Bidirectional LSTM	Temperature (at different positions) + spindle speed
	(Li et al. 2020)	GRNN	Temperature (at different positions)
	(Aggogeri, Merlo, and Pellegrini 2020)	ANN, GBT, Linear Regression, Polynomial Regression, Naïve Bayes (comparative study)	Temperature (at different positions)
	(Tian and Pan 2020)	DNN	Temperature (at different positions)
	(Wang et al. 2019a; Wang et al. 2019b; Fujishima et al. 2018)	CNN	Temperature (at different positions)
	(Blaser, Mayr, and Wegener 2019)	DBN	CNC data + temperatures + torque of machine + backlash errors
	(Fujishima et al. 2019)	DNN	Machine structure temperatures + thermal displacement
Machine tool prognostics/ anomaly detection	(Gittler et al. 2020)	k-means, GMM, DBSCAN, hierarchical DBSCAN (comparative study)	Motor current
	(Liu et al. 2020)	LSTM	Machining vibration + machine tool current + spindle load
	(Wang et al. 2020)	GMM	Feed rate + spindle speed + spindle power + machining vibration
	(Puranik et al. 2020)	DNN, Autoencoder, CNN, RNN (comparative study)	CNC data + machining vibration + machine tool current
	(Lin et al. 2019)	RNN	Vibration of rolling bearings
	(Luo et al. 2018)	SAE + BPNN	Vibration of feed drive base
	(Huang, Kao, and Chen 2018)	SVM + KNN	Vibration of ball screw drive + motor speed + motor current + axis position
	(Kißkalt et al. 2018)	GMM + HMM	Vibration of ball screw drive
Energy consumption modelling/ prediction	(Kim, Shin, and Cho 2021)	Transfer learning with SVR	process planning data + CNC data + machining power + material properties
	(Xiao et al. 2020)	SVR, ANN, GPR, CNN, SAE, DBN (comparative study)	CNC data + machining power + cutting vibration + motor temperature
	(Dietrich et al. 2020)	Linear Regression, Decision Tree, KNN, RF, ANN (comparative study)	CNC data + electric load of machine tool and components
	(Komoto, Herrera, and Herwan 2020)	KNN classifier	CNC data
	(He et al. 2020)	SVR, GPR, ELM, CNN (comparative study)	Feed rate + spindle speed + axis load + depth of cut + machine tool power
	(Bhinge et al. 2017)	GPR	Feed rate + spindle speed + depth of cut + cutting direction + cutting strategy
Surface roughness monitoring/ prediction	(Misaka et al. 2020)	GPR	Cutting speed + feed rate + depth of cut + tool shank vibration + turret bed vibration
	(Grzenda and Bustillo 2019)	Semi-supervised learning approach combined with KNN and RF	Cutting speed + feed rate + depth of cut + cutting vibration

	(Župerl and Čuš 2019)	ANFIS	Cutting chip size acquired from cutting chip images
Chatter detection/ prediction	(Yesilli, Khasawneh, and Otto 2020)	SVM, logistic regression, RF, GBT (comparative study)	Cutting vibrations
	(Oleaga et al. 2018)	ANN, regression trees, RF (comparative study)	Frequency response functions measured at different positions
Real-time error compensation	(Ge et al. 2020)	GBT	Measured machining errors
Feed drive kinematics prediction	(Zhang et al. 2021)	Deep CNN	Commanded and actual positions of feed drive
Machine tool dynamics prediction	(Finkeldey et al. 2020)	Naïve linear interpolation, Elastic net, RF, GBT (comparative study)	Frequency response functions measured at different positions
Cutting tool recognition	(Luo et al. 2020)	CNN + ELM-based Autoencoder	Cutting tool images
Surface flatness prediction	(Bustillo et al. 2021)	ANN, RBF network, Decision Trees, RF (comparative study)	Tool life + average drive power + flank wear
Cutting parameters optimization	(Jurkovic et al. 2018)	SVR, ANN, polynomial regression (comparative study)	Surface roughness + cutting force + tool lifetime
Autonomous process planning	(Shin, Kim, and Meilanitasari 2019)	ANN with transfer learning	Feed rate + spindle speed + cutting depth + energy consumption

3.3.3 Intelligent human-machine interaction

Currently, the HMIs of most commercial CNC machine tools are made as control panels that are fixed on the machine tools and only provide limited feedback information (machine status, alerts, error messages, etc.) and built-in services (some high-end machine tools offer built-in data analysis, simulations, etc.) to the operators. This has significantly limited the decision-making support and human-machine interaction capabilities of machine tools. Intelligent human-machine interaction is another key enabling technology for the servitisation of machine tools. It allows various types of manufacturing services to be efficiently delivered to humans (machine tool operators, maintenance technicians, shop floor managers, etc.) as intelligent decision-making support. Based on the service-oriented system architectures (Section 3.3.1), some intelligent human-machine interactions for machine tools have been developed in previous research, including software applications running on computers and laptops, and web applications that can be accessed through mobile devices such as smart phones and tablet computers (Table 7). However, although these types of human-machine interactions can offer decision-making support for humans, they could not provide intuitive visualization and perception of the real machining environment.

In this context, AR, as one of the key enabling technologies of Industry 4.0, plays a vital role in developing intelligent human-machine interactions for machine tools. AR is a human-computer interaction technology that overlays/augments computer-generated virtual information on the real-world environment in real time (Carmigniani and Furht 2011). By enriching the physical environment with virtual information in the user's view, AR applications significantly increase the user's engagement and interaction with intuitive and immersive perception (Azuma 1997). Today, with the rapid advancement of embedded computation and intelligence, various types of display devices can be used for AR applications, including laptops, tablet computers, smart phones, HMDs, and so forth.

In the last decade, AR applications have gained a dramatic growth in various industries such as product design, advertising and commercial, entertainment, education, architecture, and medicine (Cipresso et al. 2018). In the field of manufacturing, AR has been widely studied and applied for factory layout planning, assembly design and planning, and maintenance guidance (Nee et al. 2012). Specifically for machine tools, although the development of intelligent AR-based HMIs has not received much attention, some AR-assisted process monitoring, machining simulation, and maintenance applications have been developed. Based on the services provided by the AR applications, Table 9 summarizes existing research works on AR-assisted human-machine interactions for machine tools, including the virtual objects and data displayed, and the AR display devices used.

Table 9. Research works on AR-assisted human-machine interactions for machine tools

AR Services	Reference	Virtual objects displayed	Data displayed	AR display device
Maintenance instructions	(Kollatsch and Klimant 2021)	Machine tool components	Maintenance instructions	Tablet computer
	(Mourtzis et al. 2017)	Machine tool components	Real-time machine tool status + maintenance instructions	Tablet computer
	(Mourtzis, Vlachou, and Zogopoulos 2017)	Machine tool components + maintenance tools	Maintenance instructions	Tablet computer
	(Sanna et al. 2015)	Machine tool components	Maintenance instructions	HMD and tablet computer
Process monitoring and machining simulation	(Zhu, Liu, and Xu 2019)	Workpiece + cutting tool + tool path	Real-time process data	HMD (Microsoft HoloLens)
	(Liu et al. 2019)	Workpiece + cutting tool + tool path	Real-time process data	HMD (Microsoft HoloLens)
	(Liu et al. 2017)	Workpiece + cutting tool + tool path	Real-time process data	Computer monitor
Machining simulation	(Minoufekr et al. 2019)	Machine tool components + workpiece + tool path	--	HMD (Microsoft HoloLens)
	(Ma, Yang, and Su 2014)	Workpiece + cutting tool	--	Computer monitor
	(Kiswanto and Ariansyah 2013)	Workpiece + cutting tool	--	Computer monitor
	(Zhang, Ong, and Nee 2010)	Workpiece + cutting tool	Machining program + axes positions	Computer monitor
Process monitoring	(Olwal, Gustafsson, and Lindfors 2008)	Graphic cutting forces	Real-time process data	See-through holographic optical element overlaid on the machine window
Machine tool setup instructions	(Tzimas, Vosniakos, and Matsas 2019)	Machine tool components	Machine tool setup instructions	Computer monitor
Visualization of machine tool interior	(Sommer and Verl 2017)	Machine tool components	--	Transparent LCD display in front of machine window
Machine tool setup instructions	(Neubert, Pretlove, and Drummond 2012)	Machine tool components	--	Tablet computer
Visualization of machine tool environmental impacts	(Herrmann, Zein, and Wits 2011)	--	Environmental impact assessment	Smart phone

AR-assisted maintenance and machine tool setup instructions apply a similar approach, where virtual components and instructions are rendered onto the real-world machine tools, such as the examples shown in Figure 13(a) and (b). Marker-based tracking is usually utilized since the machine tool is fixed and the accuracy requirement is not high. For AR-assisted machining simulation, however, high-accuracy position information is critical. In this case, the real-time CNC data can be used to drive the virtual machine tool components, cutting tool, and workpiece to simulate the machining process, such as the example shown in Figure 13(c). Other real-time machine tool data collected from the CNC and sensors can also be rendered onto the machining environment to achieve intuitive process monitoring. Furthermore, focusing on the enhancement of interior process visualization, optical see-through display-based AR applications have also been attempted by some researchers. Figure 13(d) shows an example of AR-assisted machine tool interior visualization using a transparent LCD display. Nevertheless, AR-based human-machine interactions for machine tools still have not received enough attentions. Few AR-based HMIs that utilize advanced data analytics to provide intelligent decision-making support for humans have been studied.

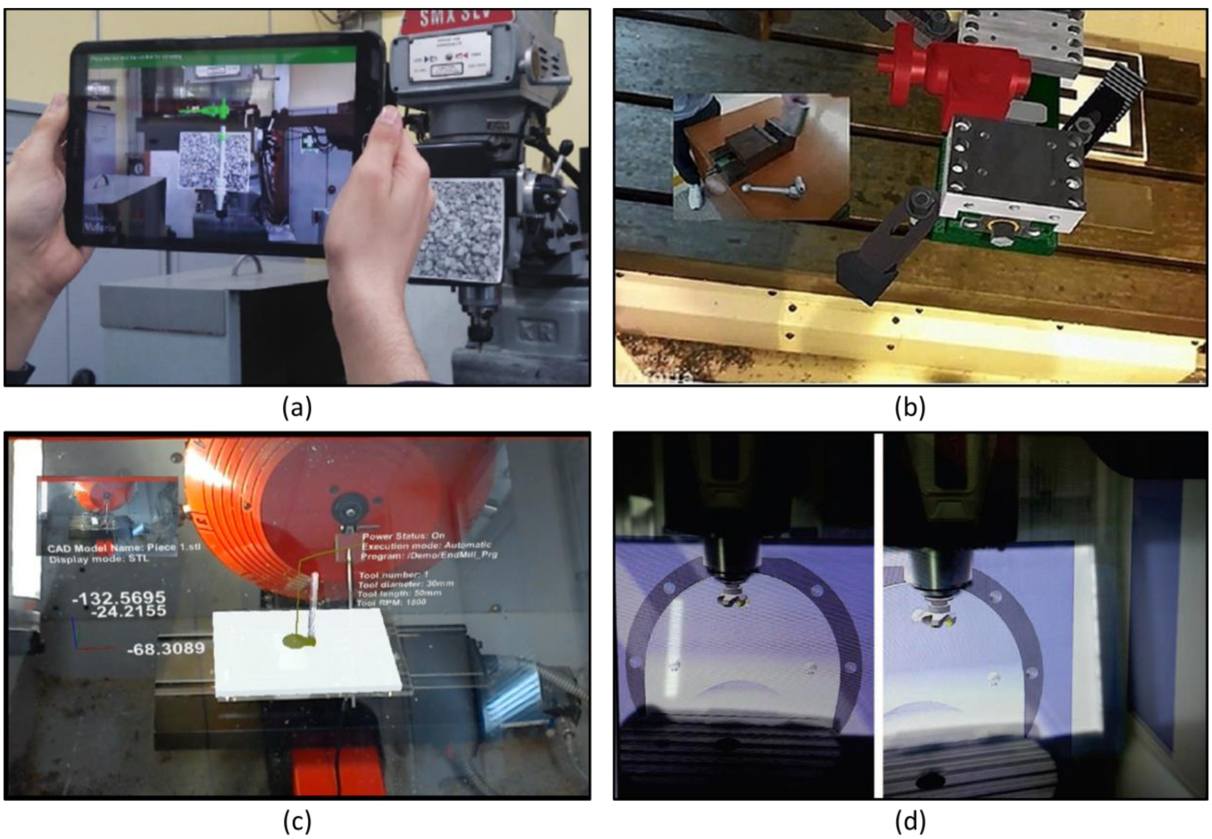

Figure 13. Examples of AR applications for machine tools: (a) Maintenance instructions (Mourtzis et al. 2017); (b) Machine tool setup instructions (Tzimas, Vosniakos, and Matsas 2019); (c) Process monitoring and machining simulation (Liu et al. 2019); (d) Visualization of machine tool interior (Sommer and Verl 2017).

4. A conceptual framework of next-generation Cyber-Physical Machine Tools

The literature review presented in Section 3 shows that a significant amount of research effort has been devoted to the digitalisation and servitisation of machine tools in the last decade. However, most existing works focus only on ad hoc functions or applications based on specific enabling technologies. From a systematic perspective, there still lacks an integral solution to the next-generation machine tools (i.e. Machine Tool 4.0) in the era of Industry 4.0. To address this research gap, we propose a conceptual framework of CPMT, which deeply integrates various key enabling technologies discussed in the previous section, as a systematic approach to achieving digitalisation and servitisation of next-generation machine tools.

Figure 14 depicts the proposed conceptual framework of next-generation CPMT. It mainly comprises three layers: physical level, edge server, and cloud services. The physical level represents the field-level manufacturing devices including the machine tool, cutting tools, workpieces, various types of sensors, and data acquisition devices. Field-level manufacturing data are collected and transferred to the edge server through different types of networks such as Ethernet and 5G. The edge server hosts the core component of the CPMT, i.e. the Machine Tool Digital Twin, as well as the edge database and the modularized intelligent algorithms. The edge server performs intelligent computing tasks using modularized intelligent algorithms and provide the results to the cloud as customizable computing services through standardized communication protocols such as MTConnect and OPC UA. In the cloud, users can request the edge computing services and configure/integrate them as customized manufacturing services (machine tool PHM, simulation and modelling, process optimization, etc.). Furthermore, results from these services can be used to support various types of AR-assisted intelligent human-machine interactions. The proposed conceptual framework represents an integral solution to the digitalisation and servitisation of next-generation CPMT. The related research issues and challenges will be discussed in the next section.

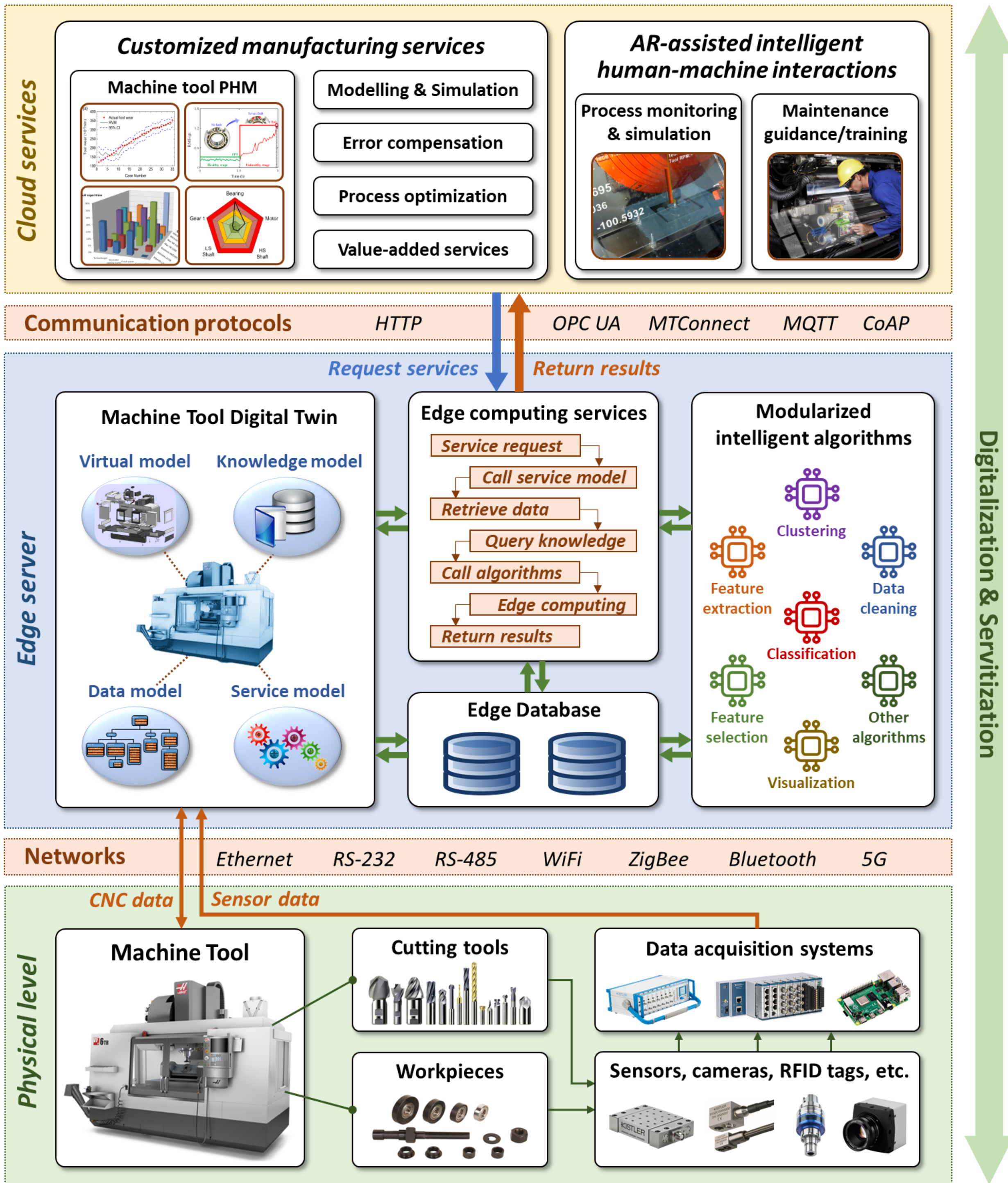

Figure 14. Conceptual framework of next-generation Cyber-Physical Machine Tools

5. Research issues and challenges

The conceptual framework of CPMT provides a system-level solution to digitalisation and servitisation of next-generation machine tools. In this section, we identify and discuss the major research issues and challenges of the digitalisation and servitisation of machine tools, which shed light on future research directions in this area.

5.1 Data acquisition

Data acquisition is the prerequisite for the digitalisation and servitisation of machine tools. Currently, reliable, efficient, and low-cost data acquisition of machine tools is still a great challenge. On the one hand, data acquisition from CNC systems is a difficult task. Standardized communication protocols that support CNC communication such as MTConnect and OPC UA have not been widely used by commercial machine tools. A collective effort from both machine tool manufacturers and third-party developers needs to be devoted to making the CNC data more open to the customers. On the other hand, sensing techniques for machining processes have not seen a significant advancement in the last decade. Most sensors and data acquisition systems have only been used in laboratories but not real-world manufacturing systems due to their high costs. Development of low-cost, reliable, accurate, and easy-to-implement sensors and data acquisition devices is an urgent need as well as a major challenge for future research.

5.2 Modelling of Machine Tool Digital Twin

Currently, there is a lack of a systematic digital twin modelling method for machine tools. Due to the complex data, functions, and knowledge involved in machine tools, modelling a multidimensional MTDT remains a great challenge. As shown in Figure 14, a typical MTDT contains a virtual model, a data model, a knowledge model, and a service model. The virtual model represents detailed 3D models of the machine tool components and describes their behaviors. MTConnect and OPC UA can be used to develop the data model while ensure interoperable data communication. The knowledge model contains the various types of machine tool knowledge (modelling, simulation, optimization, process planning, machine tool PHM, etc.). Development of the knowledge model is a complex and challenging task. A significant amount of research effort is needed to develop domain-specific knowledge models for machine tools. Ontology and knowledge graph techniques play a critical role in facilitating efficient knowledge generation, accumulation, reuse, and share. The service model represents a set of service templates that define various types of manufacturing services, including the required data, knowledge, and intelligent algorithms. Currently, few studies have been conducted in developing a generic service model for machine tools. Furthermore, integrating all these models as an integral, multidimensional, high-fidelity, and self-evolving MTDT represents a major challenge.

5.3 Advanced data analytics

Advanced data analytics is the key enabler for intelligent manufacturing services. Currently, most manufacturing services are ad hoc solutions that adopt tailored signal processing and machine learning techniques, resulting in poor flexibility and customizability. Developing modularized intelligent algorithms that have unified data input/output interfaces is a promising research direction for realizing customizable manufacturing services. For the application of machine learning methods in machine tools, there are still many issues to be addressed. The black-box nature of machine learning methods is a major hinder for their application, given the high reliability and robustness requirement of machine tools. Improving the explainability of machine learning algorithms is a great challenge in the AI field. Another critical issue is that high-quality manufacturing data for machine learning are difficult to collect and label. The data acquisition processes are usually expensive and time-consuming. Data collected from the real-world manufacturing systems are often severely unbalanced due to lack of fault conditions. Making more public high-quality machine tool datasets available is an urgent need. Furthermore, with the rapid evolvement of AI technology, selecting the appropriate machine/deep learning techniques for specific applications continues to be a challenging task.

5.4 Service-oriented development approach

Next-generation machine tools are no longer individual manufacturing equipment, but rather integrated product-service systems (Zheng et al. 2019) that can offer not only machining capability, but also various types of networked, intelligent, customizable, value-added manufacturing services such as machine tool PHM, modelling and simulation, and process optimization. There is an urgent need for a novel service-oriented development approach for the next-generation machine tools. The service-oriented edge-cloud architecture proposed in Figure 14 provides a possible solution where cloud-based customizable manufacturing services can be achieved upon the MTDT, the modularized intelligent algorithms, and the edge computing services. However, many research issues need to be addressed in future research, including the service mechanisms such as service request and response, service generation, configuration, integration, and utilization, as well as the interoperable data communication among the physical level, the edge server, and the cloud.

5.5 Human-machine interactions

Industry 4.0 does not aim at a fully autonomous manufacturing paradigm without any human intervention. On the contrary, humans will play an important role especially in high-level decision-making activities. For machine tools, various types of intelligent decision-making support services for different users (product designers, process planners, production managers, operators, maintenance technicians, etc.) need to be extensively investigated in future research. AR-assisted intuitive human-machine interactions for machine tools have shown great advantages. However, the potential of AR in combination with advanced data analytics has not been fully exploited. Integrating high-fidelity physics-based machining simulation with AR technology is also a challenging task. Overall, the roles that humans play in the era of Industry 4.0 have not been fully investigated. Extensive research needs to be conducted to explore novel forms of intelligent and intuitive human-machine interactions for the next-generation machine tools.

6. Final remarks

In the era of Industry 4.0, machine tools are expected to have a higher level of accessibility, connectivity, intelligence, adaptivity, and autonomy. In the last decade, research on machine tools has experienced a vigorous growth with the rapid development and application of various Industry 4.0 technologies. However, few review articles on the development of machine tools in the context of Industry 4.0 have been reported. To understand the current status of digitalisation and servitisation of machine tools, this paper provides a systematic literature review combining both bibliometric and qualitative analysis, aiming to answer the four research questions proposed in Section 1.

The main scientific contributions of this paper are summarized as follows. First, research trends and focuses of machine tools in the last decade are quantitively analyzed through a bibliometric analysis. Results show that research effort on machine tools has been rapidly increasing. While traditional research topics (error compensation, simulation and modelling, process control, etc.) are still being extensively studied; digitalisation and servitisation of machine tools have become a new research trend. Second, a qualitative literature review of publications on digitalisation and servitisation of machine tools is presented. The key enabling technologies, methods, standards, architectures, and applications are identified, summarized, and compared in detail. The review results provide a comprehensive and in-depth understanding of recent advancements of digitalisation and servitisation of machine tools. Third, we propose a novel conceptual framework of CPMT by deeply integrating the key enabling technologies identified in the literature review. The proposed conceptual framework provides a systematic approach to achieving digitalisation and servitisation of next-generation machine tools. Finally, major research issues and challenges are identified and discussed, which sheds light on future research directions for digitalisation and servitisation of machine tools.

In addition to the scientific contributions, this work also has significant practical implications. The review results could help machine tool manufacturers understand the cutting-edge research works on digitalisation and servitisation of machine tools in academia, identify the gaps between research focuses and practical development progress in the industry, and further integrate the key enabling technologies in their machine tools to meet the increasing customer needs for digitalisation and servitisation. Moreover, the various key enabling technologies and the conceptual framework of CPMT presented in this paper could also help third-party equipment and service providers to discover future R&D directions and new business opportunities (data acquisition and communication devices, AR-based HMIs, cloud-based machine tool PHM services, etc.) in the machine tool industry, since digitalisation and servitisation of machine tools are becoming a promising trend in the era of Industry 4.0.

It is worth mentioning that this work comes with some limitations. First, we use WoS Core Collection database as the only database to collect publication data. Although it is one of the largest and most reputable databases, a fraction of literature may have been overlooked in this literature review. Second, the development of machine tools involves a wide range of technologies from different research areas. This work focuses mainly on the ones most related to digitalisation and servitisation of machine tools. The traditional technologies for machine tools (such as error compensation, simulation and modelling, and process control) are not specifically analyzed in this work. Furthermore, this work focuses on research works in the academia, and hence omits recent advancements in the machine tool industry, though some leading machine tool manufacturers have started applying Industry 4.0 technologies in their products and services. Analysis of information from public media sources such as official websites of machine tool manufacturers and online news could be conducted in future research to further investigate the current status of digitalisation and servitisation of machine tools in the industry.

Overall, digitalisation and servitisation of machine tools represents a new technological revolution enabled by various emerging Industry 4.0 technologies. Development of the next-generation machine tools will require collaborative efforts from both academia and industry. In addition to the research issues and challenges discussed in Section 5, future research also needs to investigate three types of system-level integrations involving machine tools, including 1) vertical integration between field-level manufacturing tasks and high-level decision-making activities such as production planning, maintenance scheduling, and enterprise resource planning; 2) horizontal integration that allows machine tools to autonomously collaborate with other manufacturing devices in the shop floor; and 3) end-to-end integration throughout the engineering process encompassing design, process planning, manufacturing, assembly, etc. We hope that this work could help both researchers and industrial practitioners get a clear picture of the current status of research on digitalisation and servitisation of machine tools, and further spark new ideas for developing the next-generation machine tools in the era of Industry 4.0.

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Declaration of Competing Interest

No potential conflict of interest was reported by the authors.

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