

Review

Multisensor Data Fusion-Driven Digital Twins in Computer Numerical Control Machining: A Review

Yang Cao 

Mechanical and Industrial Engineering Department, Montana State University, Bozeman, MT 59717, USA;
yang.cao1@montana.edu

Abstract

As key equipment in the manufacturing industry, computer numerical control (CNC) machines need to meet the ever-increasing demands for high automation, intelligence, and integration. Since its introduction in 2003, digital twin (DT) has seen its broad applications in various areas, such as product design, process monitoring, quality control, and fault diagnosis. A DT creates a virtual replica of the physical system by integrating real-time data with simulation technologies, providing new possibilities to make CNC machining more intelligent. In the past decade, extensive research has been conducted on the implementation of CNC machining DTs (CNC DTs). This paper focuses specifically on multisensor data fusion-driven CNC DTs by introducing key technologies including sensors, data fusion, and CNC DT architecture. A comprehensive survey is conducted on existing studies of CNC DTs according to their application areas, followed by critical analysis on existing challenges. This review summarizes the current progress of CNC DTs and provides guidance for further development.

Keywords: multisensor data fusion; digital twin; CNC machining



Academic Editor: Panagiotis Kyratsis

Received: 15 August 2025

Revised: 16 September 2025

Accepted: 2 October 2025

Published: 6 October 2025

Citation: Cao, Y. Multisensor Data Fusion-Driven Digital Twins in Computer Numerical Control Machining: A Review. *Machines* **2025**, *13*, 921. <https://doi.org/10.3390/machines13100921>

Copyright: © 2025 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

A digital twin (DT) is a digital replica of a real-world physical process or system that serves as an effectively indistinguishable digital counterpart of it for practical purposes, such as simulation, integration, testing, monitoring, and maintenance [1]. The idea of using virtual models to simulate physical systems can be traced back to 1970 when NASA used complex modeling and simulation techniques to replicate the spaceship in the Apollo 13 mission [2]. In 2003, Michael Grieves introduced the concept of DT during a presentation at the University of Michigan on product lifecycle management development centers [3], which was called “information mirroring model” at that time. He defined it as a virtual model of a physical object, emphasizing the integration of physical and digital systems for real-time monitoring, simulation, and optimization. Before 2010, DT generally remained a pipe dream since the required computing power, connectivity, and data storage were far too expensive for most industries to implement. In 2010s, along with the advances in computation capabilities and network technologies, DT has gained wide adoption in various industries such as manufacturing, construction, energy, and automotive industries [4–9]. These industries started using DTs not only for design and simulation but also for continuous monitoring, predictive maintenance, and process optimization.

Computer numerical control (CNC) machines are core resources in the manufacturing industry. CNC machining is a subtractive manufacturing process that produces parts by removing material from workpiece stocks. It is critical to modern manufacturing for its

ability to produce accurate, reliable, and affordable parts. However, CNC machines are very complicated and require expert knowledge in their operation and maintenance. Incorrect cutting settings, worn tools, or improper maintenance not only deteriorate product quality, but can also lead to unscheduled downtime and even catastrophic failures. Traditionally, process monitoring and quality control in CNC machining have been done manually by either in-process observation or offline measurement. These methods are either restricted by limited accessibility during machining or require a lot of time for dismantling and tool setup. Since the 1960s, computer-aided design (CAD), computer-aided manufacturing (CAM), and computer-aided engineering (CAE) have represented the earliest virtual tools that were used to assist product design, manufacturing, and engineering analysis processes. Although these virtual models are not DTs in the modern sense, they laid the foundation and were later integrated as essential components in the implementation of DTs in the manufacturing sector. In the 2000s, as computing power and sensor technologies kept advancing, machine tool manufacturers like Siemens and FANUC started integrating more advanced software and sensors into CNC machines, allowing for better monitoring and optimization of machining processes. Early efforts began to align with some of the principles of the DT concept: creating a digital replica of the physical CNC machine that could simulate, monitor, and optimize its behavior [10–12]. The introduction of Internet of Things (IoT) marked a major turning point for the use of DTs in CNC machining. Multiple sensors were deployed on CNC machines to collect real-time machining signals, such as cutting forces, torques, vibrations, acoustic emission (AE), motor current, temperature. These signals were fused together to provide more precise and reliable information about machine status, machining process, and part quality.

Nowadays, smart manufacturing is becoming a major trend, which requires increasing adoption of digital technologies and artificial intelligence (AI) to enhance machining process speed, efficiency, quality, and safety [13,14]. As an important enabling technology for the successful implementation of smart machining [15], DTs provide a high-fidelity digital model of the physical machine, thus providing an effective solution to make CNC machining more efficient and intelligent. A milestone chart that shows the development of DT technologies in CNC machining is presented in Figure 1. Hence, the major motivation of this paper is to conduct a survey of the state of the art of multisensor-based DTs in CNC machining, thus providing insights for transitioning from multisensor DTs to systematic and intelligent DTs. The remainder of this paper is organized as follows. Section 2 introduces the sensors that are commonly used in CNC machining for data collection. Section 3 discusses three levels of data fusion technologies, Section 4 illustrates the architecture of CNC machining DTs (CNC DTs), and Section 5 presents recent studies on CNC DT applications. Finally, Section 6 concludes the article by presenting existing challenges and future research directions.

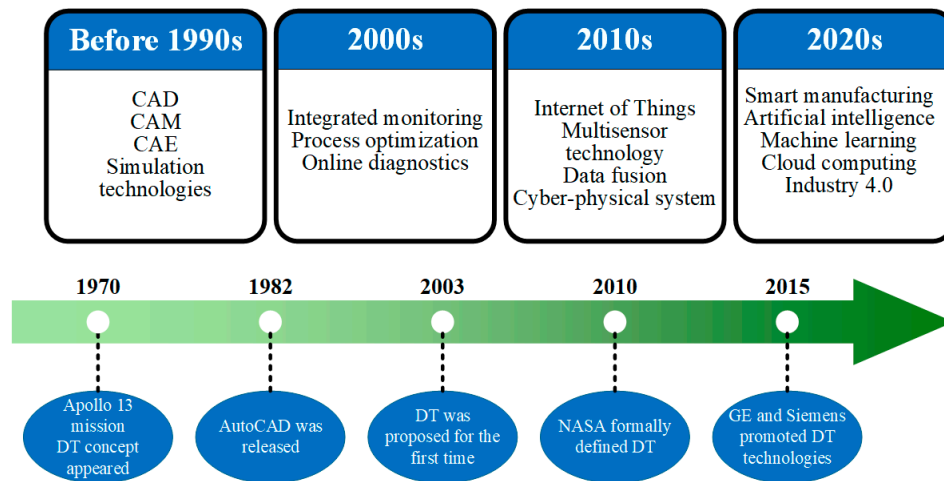


Figure 1. Milestone chart that shows the development of DT technologies in CNC machining. Bottom: key milestone events associated with the development of DT from concept proposal, technical breakthrough, to industrial applications. Top: key technologies that supported the development of CNC DTs.

2. Sensors Commonly Used in CNC Machining Monitoring

A sensor is a transducer that converts a physical phenomenon into an electrical signal. Sensors are indispensable components in CNC DTs as they collect real-time data from the physical system, which serves as the foundation to simulate, analyze, and optimize the machining process. Commonly used sensors in CNC machining monitoring include dynamometers, accelerometers, AE sensors, temperature sensors, displacement sensors, and machine vision cameras. A comparison of different types of these sensors is provided in Table 1.

2.1. Dynamometer

Cutting forces are one of the most sensitive indicators of machining performance and tool condition [16,17]. A triaxial dynamometer is usually used to measure cutting forces and torque during machining operations. Dynamometers are generally based on either strain gauges or piezoelectric materials, with the latter being considerably more expensive. A major difference between strain-gauge dynamometers and piezoelectric dynamometers is their sampling rates. The typical sampling frequency range of strain-gauge dynamometers is 1500 to 2500 Hz, whereas piezoelectric dynamometers can work at a sampling rate up to 10,000 Hz [18]. Hence piezoelectric dynamometers are more favorable in high-speed dynamic applications. Depending on their configurations, dynamometers can also be categorized into stationary dynamometers and rotating dynamometers. Stationary dynamometers are mounted between the workpiece and machining worktable to measure XYZ cutting forces acting on the workpiece. Rotating dynamometers are inserted into a machine's spindle and follow its rotation; hence, they can directly measure the cutting forces acting on tool cutting edges. Once the cutting force data is obtained, proper signal processing techniques are needed to analyze it in both time and frequency domains.

Table 1. Comparison of different types of dynamometers, accelerometers, and displacement sensors.

Types		Working Principle	Maximum Sampling Frequency	Cost	Limitations	Application Scenarios
Dynamometer	Strain-gauge	Measures strain in a material via change in resistance.	A few kHz	Low	Limited frequency response Low sensitivity Drift and noise Cannot measure static forces	Static or slow force variations Long-term monitoring
	Piezoelectric	Measures dynamic force via charge generated in piezoelectric crystals.	Tens kHz	High	Sensitive to temperature High cost	Dynamic and high-frequency measurements
Accelerometer	MEMS	Uses capacitive or piezoresistive sensing to detect motion of a miniature proof mass.	A few kHz	Low	Temperature drift and noise Low sensitivity Limited frequency response	Static or low-frequency measurements
	Piezoelectric	Uses piezoelectric materials that generate charge when stressed.	Hundreds kHz	High	Cannot measure static acceleration Bulky and expensive	High-frequency, high-accuracy dynamic measurements
Displacement sensor	LVDT	Electromagnetic induction via a moving ferromagnetic core.	Tens kHz	Moderate	Requires physical contact Limited frequency response	Contact-based applications Static or slow movement
	Eddy current	Eddy currents induced in a conductive target when it is exposed to an oscillating magnetic field.	Tens MHz	Moderate	Only works with conductive targets Sensitive to temperature drift and target material variations	Non-contact measurement of metallic targets High-speed dynamic applications
	Laser	Measures distance using reflected laser beam (triangulation or time of flight).	Hundreds kHz	High	Highly sensitive to surface reflectivity and texture Needs precise alignment and clean optical path	High-precision and non-contact measurements Applications requiring long range Measuring on non-metallic or delicate surfaces

2.2. Accelerometer

CNC machines consist of various mechanical parts, with each exhibiting specific vibration characteristics. The vibration signal in CNC machining has not only been proven to be very useful in monitoring tool conditions [19–22], controlling part quality [23,24], but is also essential for detecting and diagnosing abnormal conditions [25]. Accelerometers are commonly used to sense vibration signals. Two widely used accelerometers are piezoelectric accelerometers and microelectromechanical system (MEMS) accelerometers. When a piezoelectric accelerometer is subject to vibrations, a mass applies a force to the piezoelectric material, which causes it to output a charge that is proportional to the acceleration. The charge output is then converted into a low impedance voltage with the help of electronics. When a MEMS accelerometer undergoes acceleration, force applied to the proof mass causes it to be displaced. This displacement changes the gap between a pair of parallel electrode plates, leading to a capacitance or resistance change, which is then converted to an appropriate voltage signal [26].

2.3. Acoustic Emission Sensor

AE, also known as stress wave emission, is the production of sound and ultrasound wave radiation of a material when it undergoes deformation and fracture processes [27]. AE sensing is a noncontact method of detecting elastic energy generated from mechanical deformation induced in the machining process. Thus, detection and analysis of these stress waves can be used to locate and identify damage, fractures, and cracks. Since its discovery in the early 1950s, AE sensing has seen tremendous growth in the use of machinery condition monitoring, fault diagnosis, and quality control in manufacturing processes [28–30]. AE signals during metal cutting process can be generally classified into either continuous AE signals or burst-type AE signals [31]. Continuous AE signals are associated with plastic deformation of the workpiece as well as tool flank wear, while burst-type AE signals are often observed during crack growth in material, tool fractures, or chip breakage. The key to successful AE sensor applications is to eliminate unwanted noise and extract feature signals that are related to the targeted process parameters [32]. Piezoelectric AE sensors are the most commonly used AE sensors due to their high sensitivity and rapid response. The frequency range of AE sensors varies from 20 kHz to 1 MHz and the meaningful information of AE signals in the machining process is mostly above 100 kHz [33]. Another common type of AE sensors is microphone, but its frequency range is limited to 100 kHz [34].

2.4. Temperature Sensor

Temperature sensors are mainly used for thermal error compensation in CNC machining. Thermal errors due to internal and external heat sources are one of the main factors affecting CNC machining accuracy. Internal heat sources include the cutting process, spindle motors, friction in bearings, etc. External heat sources refer to the ambient environment. According to relevant studies [35,36], thermal deformations are responsible for 40–70% of geometric inaccuracies of machine tools. Although using thermally stable materials in the construction of CNC machine tools is a good practice to reduce these deformations, they are very expensive and can lead to other problems such as increased vibration or lower acceleration [37]. Another technique is to reduce thermal errors through numerical compensation. This approach deploys a temperature sensor network on a CNC machine and establishes a model between temperature readings and thermal deformation. Thermal error compensation is done by adjusting the position of a machine's axes according to the predicted thermal deformation errors [37–39].

2.5. Displacement Sensor

Displacement sensors are precision sensors used to measure the distance or movement of an object from a reference position, usually in terms of linear or angular displacement. These sensors play a crucial role in displacement measurement and position detection in CNC machining, such as to measure geometric error, surface quality, and thermal deformation of CNC equipment. While there are various types of displacement sensors, the displacement sensors used in CNC machining need to have high accuracy and are generally limited to contact sensors or probes such as linear variable differential transformers (LVDTs) or non-contact sensors such as eddy current sensors and laser displacement sensors. LVDTs convert linear displacement into a proportional electrical signal using electromagnetic induction. Eddy current sensors measure change in impedance that is related to the distance between the sensor and a conductive target, while laser displacement sensors use laser triangulation or time of flight to measure distance.

2.6. Machine Vision

Machine vision has been widely used in monitoring tool condition and workpiece surface roughness [40,41]. Cutting tool flank wear is generally measured offline using an optical microscope, in which the tool needs to be dismantled from the tool holder. In modern manufacturing, online monitoring using machine vision technology is preferred as it does not cause machine downtime. Traditionally, part surface roughness assessment has been done using a stylus profilometer, which requires the part to be removed from the machining equipment, so called offline measurement. Due to the advances of image processing and analysis technologies, noncontact online assessment of surface roughness can be accomplished by machine vision [40,42–44]. Evaluation of surface roughness using machine vision is based on the principle of surface texture characterization of machined surface images using texture analysis techniques to establish the relationship between these parameters with surface roughness values [45].

3. Multisensor Data Fusion

Multisensor data fusion refers to the acquisition, processing, and synergistic combination of information gathered by various sensors to provide a better understanding of a phenomenon [46]. In recent years, multisensor data fusion technology has been widely used in both military and civilian fields. Based on the level of source information being processed, data fusion can generally be categorized into data-level fusion, feature-level fusion, and decision-level fusion [47,48]. A comparison of them is provided in Table 2.

3.1. Data-Level Fusion

Data-level fusion refers to the direct fusion of various types of raw data obtained through multiple sensors. A common data-level fusion method is image fusion. For instance, Wang et al. [49] used a signal-to-image conversion method to fuse vibration signals from three channels of an accelerometer. Vibration signals from three channels during the same time segment were sampled and then converted into a grayscale image by using an image processing function. The grayscale image then underwent a deep convolutional neural network (CNN) to generate output that provided fault recognition information for rotating machinery. Azamfar et al. [50] proposed a CNN-based data-level multisensor data fusion framework for multiple current sensors. Specifically, raw frequency domain data from multiple current sensors were stacked row by row to form a matrix as the input to a CNN architecture. As the convolutional filters moved across the input matrix, information from multiple sensors was fused together for gearbox faults diagnosis.

Table 2. Comparison of data-level, feature-level, and decision-level data fusion.

	Advantages	Disadvantages	Application Scenarios	Example Algorithms
Data-level	Highest information granularity Minimal information loss	High bandwidth and computation requirements Highly sensitive to noise and sensor failures	Homogeneous sensors and real-time monitoring needs	Simple and weighted averaging Kalman filter CNN
Feature-level	Strikes a balance between information richness and processing complexity	Requires domain expertise in feature engineering and data representation	Feature extraction is reliable Retain significant information without dealing with raw data To be used with machine learning algorithms	Fuzzy inference Machine learning algorithms
Decision-level	Strong flexibility and robustness	Hard to reconcile conflicting system outputs	High-level control and strategic decisions when component systems are mature and reliable	Majority and weighted voting Bayesian probabilistic inference

Data-level fusion provides the highest granularity of information with minimal information loss, allowing downstream algorithms to exploit all the primitive data. However, the high data volume imposes challenges on bandwidth and computational requirements. Meanwhile, it is highly sensitive to noise and sensor failures [48]. Thus, data-level fusion is better suited for applications with homogeneous sensors and real-time monitoring needs.

3.2. Feature-Level Fusion

Feature-level fusion extracts feature information from raw data sources and fuses them using appropriate calculations and algorithms for subsequent decision analysis. A common practice in feature-level multisensor data fusion is that statistical features such as average, peak-to-peak, variance, maximum, kurtosis, and root mean square of original signals are extracted and used as inputs for a machine learning algorithm. For instance, Tangjitsitharoen et al. [51] developed an in-process monitoring system of the tool wear and cutting states in CNC turning process by utilizing multisensor fusion technology. The system consisted of a dynamometer, an accelerometer, an AE sensor, and a sound sensor. Energy spectrum densities of signals from the dynamometer, AE sensor, and sound sensor, the average variance of the acceleration signals, and cutting parameters were used as inputs for a two-layer neural network, and the output was the level of tool wear. Garcia et al. [52] used multiple sensors to predict part surface roughness in turning operations. Features of signals from these sensors were extracted by using different methods, such as time direct analysis, power spectral density, singular spectrum analysis, and wavelet packet transform. These features were then fused together as inputs for multiple regression and artificial neural networks. Duro et al. [34] developed a CNC machining monitoring system that was composed of three microphones. The three microphones had been positioned around the workpiece. Signals from the three microphones were filtered, normalized, and then combined by a weighted summation method. Wang et al. [53] presented a multisensor data fusion technique to predict tool wear for a milling machine. Sensor signals were obtained by a dynamometer and three accelerometers. Statistical features in time and frequency domains were extracted and fed as inputs for various machine learning algorithms to predict tool wear.

Feature-level fusion strikes a balance between information granularity and abstraction. It is a popular approach in predictive maintenance, quality control, and fault diagnosis. The advantages of feature-level fusion are, after feature extraction, the amount of data to be processed is reduced and the real-time performance is improved [48]. However, its performance depends heavily on domain expertise in feature engineering and data representation.

3.3. Decision-Level Fusion

Decision-level fusion is a high-level data fusion technique that involves integration of preliminary decisions from different sensors or methods. A common approach in decision-level data fusion is weighted summation. For example, Tian et al. [54] used decision-level data fusion for porosity prediction in laser-based additive manufacturing. High-speed thermal images of the melt pool were captured. A PyroNet based on CNNs and an IRNet based on recurrent convolutional networks were used to correlate sequential thermal images with layer-wise porosity. Predictions from PyroNet and IRNet were fused at decision-level using a weighted summation method to obtain more accurate results. Safizadeh and Latifi [55] used an accelerometer and a load cell for vibration fault diagnosis of rolling element bearings. The two sensors were used independently to obtain decision-making. Then k-nearest neighbor (KNN) classifier was used to choose the class with the highest probability. Wei et al. [56] developed a decision-level data fusion approach to predict

the surface roughness of additively manufactured components. Low-level preliminary decisions based on temperature and vibration sensor data were transformed into high-level decisions integrated by a convex optimization model.

Decision-level fusion has strong flexibility and robustness [57], which represents a feasible fusion approach when other fusion methods are not practical. It is ideal for high-level control and strategic decisions when component systems are mature and reliable, but would encounter challenges to reconcile conflicting system outputs.

4. Architecture of CNCDTs

By establishing a digital replica of a physical entity, DTs can achieve real-time interactive mapping with the physical entity and provide useful information and guidance in its full life cycle. The two key requirements of CNCDTs are real-time response and high-fidelity. Real-time DTs mean the continuous, low-latency data transmission and processing between a physical system and its digital replica, enabling dynamic updates and analytics without noticeable lag. High-fidelity refers to the degree of accuracy, detail, and realism with which the DT replicates the physical system, including accurate modeling, rich data, realistic simulation, and accurate prediction. As shown in Figure 2, a CNCDT typically consists of five components:

- (1) Physical space contains all the physical manufacturing resources, including CNC machines, sensors, electronics, and robotics.
- (2) Digital space is the digital counterpart of the physical space. By utilizing real-time manufacturing data obtained from the physical space and relevant models and algorithms in the knowledgebase, digital space can realize multiple functions such as process monitoring, process optimization, tool wear prediction, quality control, and fault diagnosis.
- (3) Communication represents the data exchanging between the physical space and digital space. Communication from physical space to digital space includes data from the CNC machine, such as process parameters, machine condition data, and data obtained via sensors. Communication from the digital space to the physical space is mainly feedback control signal used to optimize the machining operation.
- (4) Database is a container of massive manufacturing data that is related to both the physical and digital spaces. It is a support system to realize various DT-enabled applications.
- (5) Knowledgebase acts as the brain of a CNCDT by integrating models and algorithms with various DT applications. Machine descriptive models are models that are used to describe the mechanical, electrical, and hydraulic subsystems of machining equipment. Machining process models are used to understand the cutting process and achieve fault diagnosis. Tool models can be used to understand the tool wear process and achieve proactive tool changes. Part quality models are used to establish the relationship between machining process and part quality, such as dimensional accuracy and surface roughness. Most models have the capabilities of self-learning and self-improving based on new data. Algorithms are machine learning approaches to solve practical DT problems, such as linear regression, artificial neural networks, random forest, support vector machines (SVMs), etc.

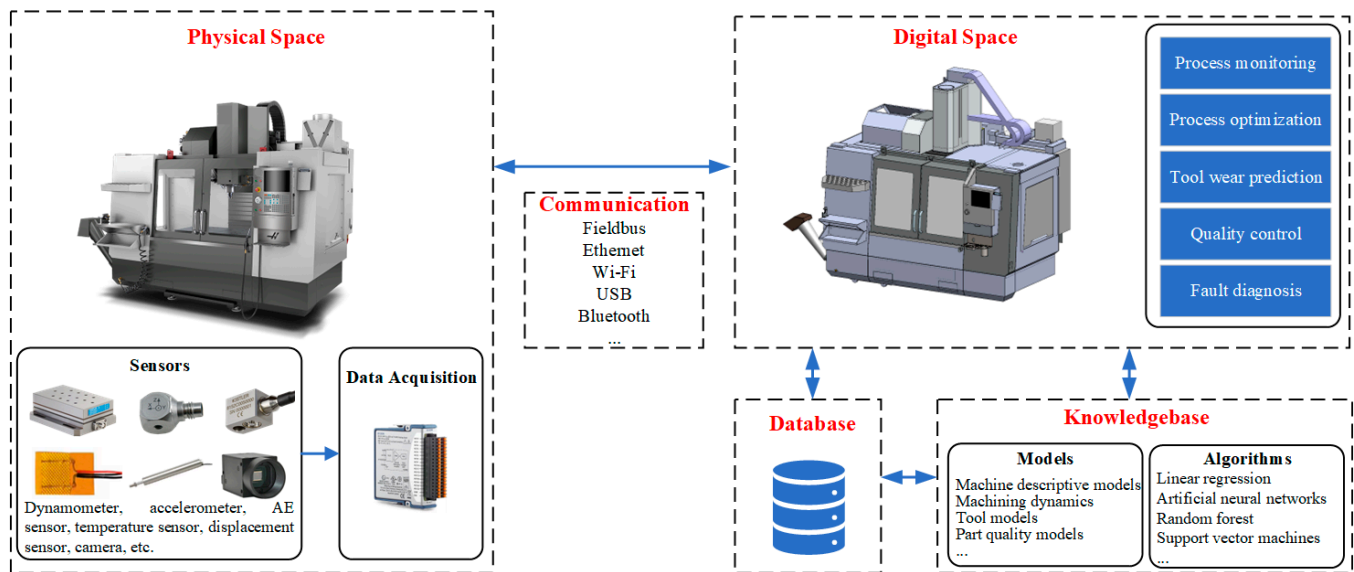


Figure 2. Architecture of CNC DTs.

5. Applications of DTs in CNC Machining

In CNC machining, DTs fuse real-time data from the physical system with digital intelligence, providing a comprehensive platform to improve machining operations. This section provides an overview of existing studies that have leveraged DTs in CNC machining applications, including machining process monitoring, machining quality control, machining process optimization and adaptive control, tool wear monitoring and prediction, and fault diagnosis and predictive maintenance (shown in Figure 3 and summarized in Table 3).

5.1. Machining Process Monitoring

Modern machining equipment is getting more automated with less dependence on human labor. The success of an automated machining system relies on a robust monitoring system for online supervision of key process parameters. Although machining simulation has been utilized in the manufacturing sector for decades, it is limited to machining process validation and toolpath generation—so called CAM. However, this offline simulation mode cannot reflect real-time process conditions, limiting its applications in intelligent machining process monitoring. The advances of DT, along with other information technologies such as IoT and augmented reality (AR), create new possibilities for real-time machining process monitoring [58]. For instance, Liu et al. [59] proposed a machining process monitoring system based on DT and AR. The system utilized AR technology to fuse virtual information with real-time physical data, promoting cooperation between operators and the DT system. Guo et al. [15] developed a DT-driven machining simulation and monitoring system based on perception-monitoring-feedback framework. Using CNC code as the simulation object, the system could monitor the cutting process, avoid tool collisions, and predict tool wear. In the machining process, many phenomena affect machine conditions and product quality, such as tool wear, chatter, and tool breakage. Many of these cutter-related failures can be detected using DT technology. For instance, chatter is a kind of self-excited vibrations that frequently occurs during machining operations, which induces severe damage to both spindle tools and workpieces [60–62]. Jauhhari et al. [63] developed a DT virtual machining system for detecting chatter by using the variational mode decomposition method, wavelet-based synchro-squeeze transform, and transfer learning application. Different features were extracted from the raw data and then fed as inputs of neural networks. The system showed 94.04% classification accuracy in the experiments. Bakhshandeh et al. [64] presented a

DT-assisted online monitoring and control system for CNC machining. The CNC and external sensor data were synchronized online with the DT data by mapping the actual tool center positions from the CNC machine to the positions in the virtual machining system. The machining process monitoring and control system was demonstrated for various applications including adaptive cutting, tool wear progression, tool breakage detection, and chatter detection. Similarly, Bai et al. [65] developed a DT-based tool wear monitoring and chatter detection system, in which cutting forces and vibration data were used to estimate tool wear and detect chatter, respectively.

Compared with traditional machining process monitoring that highly relies on manual inspection and operator experience, DT-based machining process monitoring combines sensor data, machine parameters, historical data, CAD/CAM models, and optimizes machining systems in a more automated and proactive manner. Despite these advantages, several limitations persist. Most notably, the accuracy of DTs depends heavily on high-quality, real-time data and robust modeling techniques. Challenges such as data integration across heterogeneous systems, high computational requirements, and limited interoperability with legacy CNC machines hinder widespread deployment. Many existing implementations are tailored to specific machines or processes, limiting scalability and generalizability.

5.2. Machining Quality Control

In-process quality monitoring and assurance plays a significant role in intelligent manufacturing. One of the most critical quality characteristics in CNC machining is geometric accuracy. In CNC machining, dynamic error refers to the difference between the commanded tool path and the actual tool path, which could arise from the servo system or caused by external factors such as machine structure flexibility, vibrations, and thermal deformation. DT offers a possibility to achieve online monitoring of these variations and utilize online adjustments to eliminate post-process quality control. This is crucial for improving productivity and reliability, and reducing production times and costs [66]. For example, Irino et al. [67], Zhang et al. [68], and Zheng et al. [69] utilized DT technology to compensate for dimensional errors caused by thermal deformation in CNC machining. Luo et al. [70] presented a predictive DT-driven dynamic error control approach for accuracy control in slow-tool-servo ultraprecision diamond turning. The total dynamic error was predicted using in-line acceleration data near the tool and a feedforward controller was used to mitigate the total dynamic error. Recently, digital threads have emerged as a promising solution to integrate multi-dimensional and multi-process data [71]. In multi-process machining, error propagation between different processes presents challenges to current DT systems. To address this issue, Lin et al. [72] developed digital threads to identify machining states and analyze error evolution and implement effective closed-loop control. DT-based adaptive control to ensure geometric accuracy is essential for thin-walled parts such as impellers and blisks, among others in the aerospace industry. Machining thin-walled or slender parts is challenging because the cutting forces causes excessive part deformation that significantly influences machining accuracy. Therefore, it is of great significance to develop an effective online deformation detection and compensation method to ensure machining quality and accuracy. Zhang et al. [73] built a DT-based online optimal control method for milling deformation of thin-walled parts. Multidimensional DT modeling, knowledge-driven milling deformation simulation, and milling deformation optimal control were introduced as the three key technologies. The framework took into consideration both deformation and force data and could realize real-time deformation perception, high-fidelity and low-latency simulation, and online optimal process control to improve machining accuracy of thin-walled parts. Abed et al. [74] introduced a feedback loop

that integrated DT to adjust toolpath to correct machining errors in milling low-stiffness structures. When milling a low-rigidity structure, the cutting forces and vibrations lead to dimensional errors that significantly impair parts' geometric accuracy. Traditional methods either use lower material removal rate or post corrective run to correct geometric errors. The proposed approach utilized DT to estimate 3D deformations by fusing cutting force signal in XYZ directions and corrected the toolpath automatically. As a case study, the DT-in-the-loop method was tested on an end milling operation of low-stiffness component. Experimental results showed that the proposed method significantly reduced geometric errors by 78.96%. Li et al. [75] considered both the milling force and the time-varying effect of tool wear in the dynamic error compensation in the machining of impeller blades, where features were extracted and fused from multiple sensors. Similarly, Lu et al. [76] utilized DT technologies to monitor the surface quality of slender parts in turning operations. Quality and productivity are usually two competing factors in manufacturing. Utilizing an uncertainty-aware DT, Kim et al. [77] proposed an intelligent feed rate optimization that maximized productivity while maintaining quality under desired servo error constraints and stringency. The DT was able to incorporate known uncertainty from physics-based models and learn unknown uncertainty using an online data-driven model to predict contour error's distribution. Based on the uncertainty estimation from the DT, the intelligent feed rate optimization framework was capable of maximizing feed rate while accurately constraining contour error under desired tolerance and stringency. Other than geometric accuracy, surface roughness is another important quality characteristic in machining operations. Liu et al. [78] developed a DT-based surface roughness prediction and process parameter adaptive optimization method for CNC machining. A DT containing machining elements was first constructed to monitor the machining process and served as a data source for process parameter optimization. Then a prediction model based on a hybrid machine learning technique was used to realize surface roughness prediction by feeding cutting conditions and sensor data as inputs. The DT system could perform adaptive optimization of cutting parameters based on the predicted surface roughness. Zhao et al. [79] proposed a surface roughness prediction model based on pigeon-inspired optimization and SVM. Machine parameters, along with average cutting force, were fed as inputs. The model had self-learning ability to keep increasing the prediction accuracy by feeding more training data. A machining parameter self-adaptation adjustment method based on DT was proposed to stabilize the machined surface quality.

Although DT-based machining quality prediction can reduce reliance on post-process inspection, its accuracy is often compromised by sensor noise or limited model generalization across different machining equipment, cutting conditions, or materials. High-fidelity quality prediction requires extensive computational resources and accurate physical models, which are often not feasible in small and medium-sized enterprises (SMEs). These DT models may not capture subtle machine tool degradation or environmental factors that affect part quality. Any practical DT-based quality control system needs to support closed-loop control, where in-process quality predictions trigger real-time adjustments to machining parameters (e.g., feed rate, spindle speed, cutting depth) to maintain part quality. Despite the theoretical advantages, real-world implementations of closed-loop DTs for quality control are rare. Lack of standardized integration between DTs and CNC controllers poses a significant barrier.

5.3. Machining Process Optimization and Adaptive Control

In traditional machining practice, cutting parameters are pre-determined and stay constant during the machining process. Recently, there has been a desire for adaptive machining in which cutting parameters are adjusted dynamically according to variable pro-

cess conditions, in order to maintain constant spindle load. Benefits of adaptive machining include improved surface quality, reduced manufacturing cycle times, and prevention of tool breakage [80]. In addition, a tool monitoring adaptive control system can adjust feed rate based on the tool wear condition. DTs can be utilized in both spindle load-based and tool wear-based adaptive machining. For example, Tong et al. [81] proposed a DT-driven cutting force adaptive control approach for milling process. A virtual machining system was developed to predict cutter-workpiece engagement conditions. The actual cutting force was estimated based on the feed driven current and other machine parameters, and the feed rate was adjusted accordingly to maintain the cutting force at the desired value. Besides spindle load, other objectives that are considered in adaptive machining include energy consumption [82] and machine-induced residual stress [80]. Vishnu et al. [82] built a DT model to predict two key performance indicators, energy consumption and surface roughness, in CNC machining. Various machine learning methods, including SVM, fully connected deep neural network, and gaussian process regression, were used to establish the relationship between process parameters and performance indicators. The built models can be used to optimize process parameters to improve key performance indicators. Ward et al. [80] used DT technology for adaptive feed rate control in a CNC machining center to achieve stable cutting conditions. Instead of relying on real-time external sensor data, the DT model utilized internal data such as position information and cutting parameters from the machine to estimate real-time cutting force and spindle power. The limitation of this method is that the simulation of the cutting force was based upon a theoretical model, therefore accuracy is not guaranteed.

DTs turn machining from a rule-based, pre-planned activity into an intelligent, self-adjusting process. Compared with traditional manufacturing practice that follows pre-programmed parameters, DT-assisted process optimization and adaptive control generally strike a better balance between conflicting objectives such as cycle time vs. surface quality, tool life vs. cutting speed, and energy consumption vs. productivity. Nonetheless, existing applications of DTs in machining process optimization and adaptive control are often built using simplified physics-based models or data-driven models that cannot capture the full complexity of dynamic machining processes. Meanwhile, integration with existing CNC controllers and legacy systems remains a challenge. Introducing adaptive control strategies to existing CNC equipment can cause instabilities if the DT model is not precisely calibrated or if sensor latency is significant.

5.4. Tool Wear Monitoring and Prediction

Many tool issues affect product quality, such as tool wear, chatter, and tool breakage. These issues degrade the quality of machined parts and cause unscheduled machine downtime, and even lead to catastrophic tool failures [83]. Conventionally, tool changes have been conducted regularly at a frequency that is determined by operators. Early replacement of a workable tool wastes resources and increases downtime, while late replacement of a worn tool results in lower quality workpieces. Certain types of downtime that are caused by excessive tool wear during the machining operations can be avoided by implementing a tool condition monitoring (TCM) system. TCM systems are developed to monitor tool conditions and predict tool life by acquiring appropriate in-process signal and utilizing pattern recognition techniques, thereby reducing machine downtime by implementing scheduled tool changes. TCM in machining processes has been studied for over 30 years, which generally can be categorized into either direct methods or indirect methods [21,41]. Direct methods use optical equipment and machine vision technology to directly observe the tool. For example, a microscope can be used to capture tool images which are then evaluated by image analysis technology. Direct methods have a high degree

of accuracy [84] because they can directly measure the tool geometry. Despite its popularity, direct assessment of cutting tools using machine vision remains a challenge since the cutting area is not always accessible during the machining operation, in addition to the presence of coolant and cutting chips [85]. In contrast to direct methods, indirect methods are based on the relevance of sensor signals (e.g., cutting forces, vibration signals, and AE) for tool wear conditions [86]. In this method, a variety of sensors are deployed to continuously monitor machining signals, such as cutting forces, vibrations, AE, and so on. DT combines physical knowledge with data-driven intelligence, providing a new paradigm for implementing TCM [87]. Kumar et al. [88] developed a DT model to monitor the tool condition of a lathe. Several sensors including thermocouples, dynamometers, acoustic sensors, speed sensors, and vibration sensors were used for data collection, which was fed to an Arduino based data acquisition platform. The raw data was then fused by different machine learning algorithms such as KNN, SVM, random forest, multilayer perception, and CNN. This model was then used for analyzing and detecting tool condition changes. Zi et al. [89] proposed a DT-based cutter wear monitoring system for milling operations. Feature signals of the machining process were gathered through sensors in real-time, which were combined with a DT system to predict the tool wear state. Natarajan et al. [90] proposed a DT-driven TCM system for milling processes. It collected sensor data from an accelerometer and a microphone. Features extracted from sensor data were fed as inputs to different machine learning algorithms to predict tool wear values. Zhuang et al. [91] presented a DT-driven tool wear monitoring and prediction model for turning processes. A virtual cutting tool model was built to simulate the cutting process, and data fusion technologies (feature extraction and selection) were utilized to ensure the agreement between physical and virtual systems. Tool wear classification and prediction were presented based on various machine learning algorithms. Liu et al. [92] built a DT-based TCM system consisted of three parts: the physical product, the virtual product, and data flow connections. The physical product represents the machining processes; The virtual product provides real-time tool condition monitoring based on vibration data collected during the machining processes as well as its model frequency features. The data flow connections involve vibration data and machine tool numerical controller signals, which are fused at the data level.

DT-based TCM systems often suffer from over-reliance on labeled training data, which is scarce and costly to generate for every tool-workpiece combination. Most existing research was based on specific tool types, cutting conditions, and materials, while lacking generalizability when transferred to other situations. The accurate monitoring and prediction of tool wear relies heavily on machine learning algorithms. These algorithms learn from extensive and reliable data collected under real industrial conditions. Hence, the challenges to achieve reliable and robust data acquisition and processing, and algorithm selection and tuning must be resolved before DTs can be implemented widely in TCM systems.

5.5. Fault Diagnosis and Predictive Maintenance

CNC machine tools are complex with highly coupled structures, variable working environments, and different failure modes. The relationship between machine signal and fault causes is intricate and implicit. The long diagnosis and repairing time significantly reduces machining efficiency and productivity. Therefore, it is critical to implement reliable online fault diagnosis of CNC machine tools using DT technologies. Xue et al. [93] developed a DT system consisted of a mechanical subsystem, an electrical control subsystem, and a heat transfer subsystem. In practice, it is hard to accurately reflect the state of these physical systems since they are constantly changing due to variations in working conditions, machining processes, and material properties. Therefore, this study developed a DT model library in which each model mapped one possible state of the physical system.

Additionally, a model selector was trained using the DT dataset, and sensor data was used as input to determine the model that best matched with the monitoring data. Finally, the built model was used to effectively diagnose the stiffness deterioration of the spindle during CNC operations. Predictive maintenance is an effective method to avoid faults and improve the reliability of CNC machines. The transition from reactive repairing to proactive maintenance minimizes machine downtime, extends machine lifetime, and improves enterprise profitability and competitiveness [94]. Nowadays, predictive maintenance has become a new trend of prognostic and health management for complex equipment [95]. Based on multisensor data fusion, utilizing real-time model-based simulation models with live process data has demonstrated improved performance. Luo et al. [96] proposed a hybrid predictive maintenance method for CNC machine tools. A DT model was first built to simulate the actual working conditions, and DT data was gathered by different types of sensors. Then the simulated data and sensing data were fused by a particle filtering algorithm for reliable predictive maintenance. Aivaliotis et al. [97] presented a DT model to calculate the remaining useful life (RUL) of machinery equipment for predictive maintenance. The resources and properties of the machinery equipment were first modeled in a DT environment that could simulate the real machine's behavior. Data was gathered by machines' controllers and external sensors to be used for the synchronous tuning of the DT model.

The success of fault diagnosis and predictive maintenance largely relies on a high-fidelity modeling of the physical system. However, most existing research has focused on individual components of the CNC machine tools with oversimplified models that overlooked the coupling between different components, which could lead to inaccurate results. Creating a high-fidelity DT is computationally intensive and requires deep domain knowledge. Inaccurate modeling—either due to oversimplification or incorrect assumptions—can lead to misleading diagnostics or predictions. Moreover, many existing DT systems are overly reliant on historical data and lack adaptability to new materials, cutting conditions, or unforeseen operational anomalies.

Table 3. Applications of DTs in CNC machining.

Applications	Sensors Used	Data Fusion	Key Performance	Limitations	Refs.
Machining process monitoring	Accelerometer, dynamometer, strain gauge, temperature sensor, laser scanner	Data-level	AR was utilized to fuse virtual information with real physical information to monitor product quality.	No deep integration or human–computer interaction.	[59]
	Accelerometers	Feature-level	Chatter detection with an average classification accuracy of 94.04%.	The model needs pre-training and has high computational complexity.	[63]
	Accelerometer, current sensor	Data-level	Adaptive cutting force control, tool wear tracking, tool breakage detection, chatter detection and avoidance.	Most functions were not evaluated for accuracy and robustness.	[64]
	Dynamometer, accelerometer, microphone	Data-level	The proposed method could accurately estimate tool wear and detect chatter.	Study was based on laboratory conditions and lacked deep data processing and fusion.	[65]
Machining quality control	Temperature sensors, dynamometer	Data-level	After thermal error compensation, geometric accuracy was enhanced from $\pm 15 \mu\text{m}$ to $\pm 3 \mu\text{m}$.	More than 20 sensors were used. The experiment was based on certain cutting conditions.	[67]
	Temperature sensors, displacement sensors	Data-level	After thermal error compensation, geometric accuracy was enhanced from $\pm 30 \mu\text{m}$ to $\pm 3 \mu\text{m}$.	The model was based on a specific CNC machine and certain cutting conditions.	[68]
	Displacement sensors, temperature sensors	Data-level	Achieved over 90% accuracy in predicting thermal error and 72% increase in machining accuracy.	Study was done in stable laboratory environment. Did not investigate how cutting forces impact spindle heating and thermal error.	[69]
	Accelerometer, temperature sensor, current sensor	Data-level	Successfully ensured that the errors in 1280 processes of the case study remained within the tolerance range.	Cannot capture highly nonlinear or chaotic error behaviors. Error propagation modeling cannot be applied across different domains.	[72]
	Force sensor, displacement sensor	Data-level	Achieved low-latency milling deformation simulation and online optimal control of milling deformation.	Performance of the model was not rigorously evaluated.	[73]
	Dynamometer, displacement sensor	Data-level	Dimensional errors were reduced by 78.96%.	The model has high system complexity and computational requirements.	[74]
	Accelerometer, AE sensor	Feature-level	Dimensional errors were reduced by 20%.	Other processing factors such as surface roughness and tool life were not taken into account.	[75]
	Displacement sensor, microphone	Data-level	Synchronous monitoring of the diametrical errors and early chatter vibrations in turning of a slender workpiece.	Only surface quality monitoring was achieved, without feedback control.	[76]

Table 3. Cont.

Applications	Sensors Used	Data Fusion	Key Performance	Limitations	Refs.
	Accelerometers, optical linear encoders	Data-level	Cycle time was reduced by 38% without compromising error tolerances.	Several assumptions were made in the methodology.	[77]
Machining process optimization and adaptive control	None (internal sensors)	N/A	Closed-loop control of machine-induced residual stress.	Simulation of the cutting force was based upon a theoretical model.	[80]
	Current sensor	Data-level	Cutting forces were accurately controlled around the desired value of 120 N.	The average force was controlled, not peak force. The stability of the control system needs improvement.	[81]
Tool wear monitoring and prediction	Temperature sensor, dynamometer, AE sensor, accelerometer, speedometer	Data-level	Cutting forces and tool wear could be predicted in real-time.	The processing time and prediction results were strongly influenced by the frequency of the sensors, processors, and selection of algorithms.	[88]
	Dynamometer, accelerometer	Feature-level	Tool wear prediction with an accuracy of 96% and prediction time was below 0.1 s.	The experiments were conducted in laboratory environment with less variations.	[89]
	Accelerometer, microphone	Feature-level	Tool wear prediction accuracies of five machine learning algorithms varied from 83% to 91%.	The experiments were based on fixed cutting conditions, material, and tool.	[90]
	Dynamometer, accelerometer, thermal camera	Feature-level	Tool wear classification and prediction were achieved.	The model has simplified the physical system, without considering variations caused by the environment and working conditions.	[91]
	Accelerometers	Data-level	A DT-based anomaly detection and real-time TCM.	Slow modeling analysis and simple machining conditions.	[92]
Fault diagnosis and predictive maintenance	Displacement sensors, speed sensor, temperature sensors, force sensors, accelerometers	Data-level	The stiffness deterioration of the spindle during operation was effectively diagnosed.	Adaptive interaction based on fault diagnosis information was not achieved.	[93]
	Accelerator, dynamometer, AE sensor	Feature-level	A DT model was built to predict the RUL of cutting tools.	Only the predictive maintenance of cutting tools was realized.	[96]
	Photoelectric sensors, proximity sensors, vision sensors	Data-level	A DT model was built to calculate the RUL of machinery equipment.	Only the predictive maintenance of cutting tools was realized.	[97]

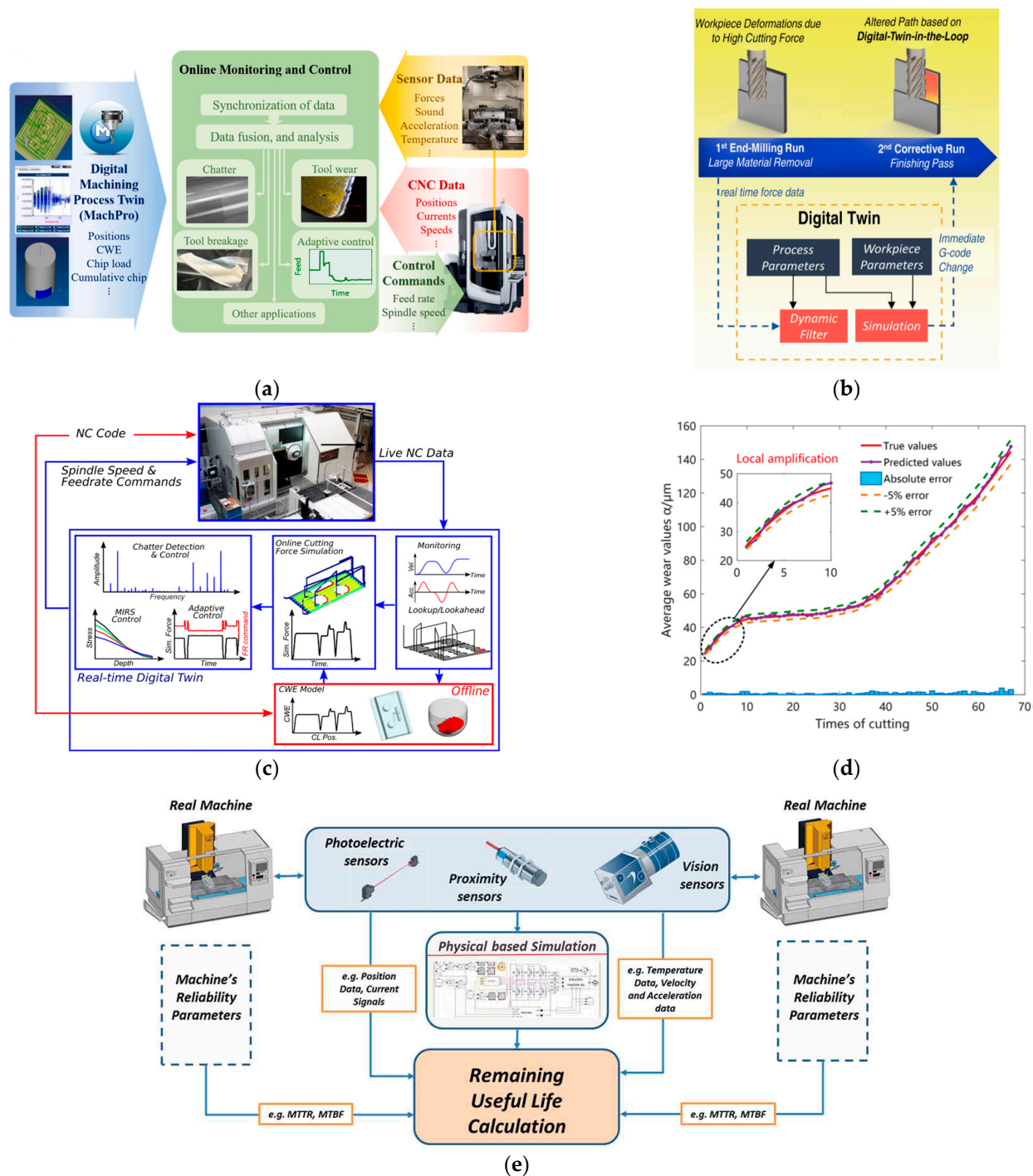


Figure 3. Applications of DTs in CNC machining. (a) Machining process monitoring [64]; (b) machining quality control [74]; (c) machining process optimization and adaptive control [80]; (d) tool wear monitoring and prediction [89]; (e) fault diagnosis and predictive maintenance [97].

6. Conclusions and Future Directions

This paper reviews the state of the art of DT research in CNC machining. Sensors that are commonly used in CNC DTs for data collection are introduced, multisensor data fusion technologies at different levels are explained, architecture of CNC DTs is illustrated, and various applications of DTs in CNC machining are reviewed in detail. Based on the review, existing issues and possible future research directions of CNC DTs are summarized below.

- (1) **Standardization:** Numerous DT frameworks have been proposed for CNCDTs, but very few have gained industrial adoption. One of the major setbacks is that there is no widely agreed standard on the technology architecture of CNCDTs. Other similar issues include communication protocols between different systems, integration technologies with existing CAD/CAM/CAE, and manufacturing execution systems (MESs) and enterprise resource planning (ERP) systems. Although various communication protocols such as Ethernet/IP [64,81,89], Open Platform Communications Unified Architecture (OPC-UA) [64,65,78,82,98], and MTConnect [73,82,98] have been utilized in CNC DT applications, they are not universally supported by CNC equipment. Standardization of CNC DT architecture and protocols is extremely important for its wide applications. There should also be standards to assess DTs since high-fidelity modeling is the foundation for reliable applications.
- (2) **System integration:** The majority of existing CNC DT research has been focused on individual machining tools and discrete functions, e.g., process monitoring, tool wear prediction, quality control. These DTs can hardly meet the requirements of modern highly integrated and interconnected manufacturing systems. Future research should focus on implementing system-level DTs, integrating multiple DTs together, and constructing comprehensive DT platforms that can provide entire lifecycle services ranging from product design and the manufacturing process to post-manufacturing maintenance.
- (3) **Data accessibility:** Data is the foundation for CNCDTs. Most CNC machines, especially legacy ones, are isolated manufacturing resources that have limited communication with external systems and need expensive retrofitting. The available data is often very limited and highly heterogeneous, making it challenging to synchronize and integrate with modern systems. More studies need to be done on sensor deployment, communication protocols, data acquisition, and data fusion in order to facilitate data accessibility in implementing CNC DTs.
- (4) **Artificial intelligence:** Machining data is becoming more and more abundant thanks to the continued development of sensor and network technologies. Nonetheless, deep fusion and utilization of data to obtain valuable information is still limited. AI is essential in the implementation of DTs so that the digital replica effectively mirrors the status of the physical machine, thus enabling more efficient and intelligent manufacturing. Despite the maturity of AI technologies, many manufacturers are still hesitant to entirely rely on AI and machine learning algorithms, due to their lack of interpretability and transparency. Under these circumstances, explainable AI (XAI) [99,100] could provide a promising solution to make the decision-making processes and outcomes of AI systems more understandable and interpretable.
- (5) **Human-machine interactions:** Humans play a crucial role in DTs even in highly automated and intelligent manufacturing systems. In most existing DT studies, humans are still not considered systematically. By integrating humans into DTs, we ensure these systems are not only technological advanced, but also user-friendly, safe, and aligned with human needs and behaviors.
- (6) **Cybersecurity:** There are a lot of digital assets and sensitive data in DTs, which often interconnect with other IoT devices and cloud services. Protecting these assets and systems from cyberattacks is essential to ensure the security, reliability, and integrity of the DT systems. Hence, more research needs to be conducted in cybersecurity strategies, enhanced encryption, and secure communication protocols.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Digital Twin. Available online: https://en.wikipedia.org/wiki/Digital_twin (accessed on 20 June 2024).
2. Li, L.; Aslam, S.; Wileman, A.; Perinpanayagam, S. Digital twin in aerospace industry: A gentle introduction. *IEEE Access* **2021**, *10*, 9543–9562. [CrossRef]
3. Grieves, M. Digital twin: Manufacturing excellence through virtual factory replication. *White Pap.* **2014**, *1*, 1–7.
4. Javaid, M.; Haleem, A.; Suman, R. Digital twin applications toward industry 4.0: A review. *Cognit. Rob.* **2023**, *3*, 71–92. [CrossRef]
5. Opoku, D.G.J.; Perera, S.; Osei-Kyei, R.; Rashidi, M. Digital twin application in the construction industry: A literature review. *J. Build. Eng.* **2021**, *40*, 102726. [CrossRef]
6. Son, Y.H.; Park, K.T.; Lee, D.; Jeon, S.W.; Do Noh, S. Digital twin-based cyber-physical system for automotive body production lines. *Int. J. Adv. Manuf. Technol.* **2021**, *115*, 291–310. [CrossRef]
7. Cimino, C.; Negri, E.; Fumagalli, L. Review of digital twin applications in manufacturing. *Comput. Ind.* **2019**, *113*, 103130. [CrossRef]
8. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* **2021**, *58*, 346–361. [CrossRef]
9. Ghenai, C.; Husein, L.A.; Al Nahlawi, M.; Hamid, A.K.; Bettayeb, M. Recent trends of digital twin technologies in the energy sector: A comprehensive review. *Sustain. Energy Technol. Assess.* **2022**, *54*, 102837. [CrossRef]
10. Martinov, G.M.; Grigor'ev, A.S. Diagnostics of cutting tools and prediction of their life in numerically controlled systems. *Russ. Eng. Res.* **2013**, *33*, 433–437. [CrossRef]
11. Jiang, J.; Kong, C.; Zhou, X.; Liu, W.; Niu, Q. Research on key technology of CNC machine tool intelligent monitoring system for smart factory. In *Advances in Manufacturing Technology XXXI: Proceedings of the 15th International Conference on Manufacturing Research, Incorporating the 32nd National Conference on Manufacturing Research, London, UK, 5–7 September 2017*; IOS Press: Amsterdam, The Netherlands, 2017; pp. 142–147.
12. Martinov, G.M.; Martinova, L.I. Trends in the numerical control of machine-tool systems. *Russ. Eng. Res.* **2010**, *30*, 1041–1045. [CrossRef]
13. Kim, D.H.; Kim, T.J.Y.; Wang, X.; Kim, M.; Quan, Y.J.; Oh, J.W.; Min, S.H.; Kim, H.; Bhandari, B.; Yang, I.; et al. Smart machining process using machine learning: A review and perspective on machining industry. *Int. J. Precis. Eng. Manuf. Green Technol.* **2018**, *5*, 555–568. [CrossRef]
14. Cheng, K.; Niu, Z.C.; Wang, R.C.; Rakowski, R.; Bateman, R. Smart cutting tools and smart machining: Development approaches, and their implementation and application perspectives. *Chin. J. Mech. Eng.* **2017**, *30*, 1162–1176. [CrossRef]
15. Guo, M.; Fang, X.; Hu, Z.; Li, Q. Design and research of digital twin machine tool simulation and monitoring system. *Int. J. Adv. Manuf. Technol.* **2023**, *124*, 4253–4268. [CrossRef]
16. Yamato, S.; Kakinuma, Y. Precompensation of machine dynamics for cutting force estimation based on disturbance observer. *CIRP Ann.* **2020**, *69*, 333–336. [CrossRef]
17. Petre, I.M.; Găvrus, C. Influence of the cutting force upon machining process efficiency. *Mater. Today Proc.* **2023**, *72*, 586–593. [CrossRef]
18. The Right Technology to Monitor Machining Processes. Available online: <https://www.kistler.com/US/en/rotating-dynamometers-piezo-vs.-strain-gauge-technology/C00000576>. (accessed on 2 June 2024).
19. Huang, Y.W.; Yeh, S.S. Development of insert condition classification system for CNC lathes using power spectral density distribution of accelerometer vibration signals. *Sensors* **2020**, *20*, 5907. [CrossRef] [PubMed]
20. Swain, S.; Panigrahi, I.; Sahoo, A.K.; Panda, A.; Kumar, R. Effect of tool vibration on flank wear and surface roughness during high-speed machining of 1040 steel. *J. Fail. Anal. Prev.* **2020**, *203*, 976–994. [CrossRef]
21. Shen, Z.A.; Cheng, J.; Tang, C.T.; Lin, C.L.; Juang, C.F. Real-time estimation of machine cutting tool wear. *J. Chin. Inst. Eng.* **2022**, *45*, 117–130. [CrossRef]
22. Ghule, G.; Ambhore, N.H.; Chinchankar, S. Tool condition monitoring using vibration signals during hard turning: A review. In *Proceedings of the International Conference on Advances in Thermal Systems, Materials and Design Engineering, Mumbai, India, 21–22 December 2017*.
23. Misaka, T.; Herwan, J.; Ryabov, O.; Kano, S.; Sawada, H.; Kasashima, N.; Furukawa, Y. Prediction of surface roughness in CNC turning by model-assisted response surface method. *Precis. Eng.* **2020**, *62*, 196–203. [CrossRef]
24. Susai, M.J.; Sai, B.; Dinakaran, D. Prediction and geometric adaptive control of surface roughness in drilling process. *FME Trans.* **2019**, *47*, 424–429. [CrossRef]

25. Albarbar, A.; Mekid, S.; Starr, A.; Pietruszkiewicz, R. Suitability of MEMS accelerometers for condition monitoring: An experimental study. *Sensors* **2008**, *8*, 784–799. [CrossRef]
26. MEMS, vs. Piezoelectric Accelerometer. Available online: <https://www.labfront.com/article/mems-vs-piezoelectric-accelerometer>. (accessed on 2 June 2024).
27. Zhou, Y.; Orban, P.; Nikumb, S. Sensors for intelligent machining—a research and application survey. In Proceedings of the 1995 IEEE International Conference on Systems, Man and Cybernetics. Intelligent Systems for the 21st Century, Vancouver, BC, Canada, 22–25 October 1995.
28. Dornfeld, D. Application of acoustic emission techniques in manufacturing. *NDT E Int.* **1992**, *25*, 259–269. [CrossRef]
29. Ali, Y.H.; Rahman, R.A.; Hamzah, R.I.R. Acoustic emission signal analysis and artificial intelligence techniques in machine condition monitoring and fault diagnosis: A review. *J. Teknol.* **2014**, *69*, 121–126. [CrossRef]
30. Kishawy, H.A.; Hegab, H.; Umer, U.; Mohany, A. Application of acoustic emissions in machining processes: Analysis and critical review. *Int. J. Adv. Manuf. Technol.* **2018**, *98*, 1391–1407. [CrossRef]
31. Inasaki, I. Application of acoustic emission sensor for monitoring machining processes. *Ultrasonics* **1998**, *36*, 273–281. [CrossRef]
32. Guo, Y.B.; Ammula, S.C. Real-time acoustic emission monitoring for surface damage in hard machining. *Int. J. Mach. Tools Manuf.* **2005**, *45*, 1622–1627. [CrossRef]
33. Li, X. A brief review: Acoustic emission method for tool wear monitoring during turning. *Int. J. Mach. Tools Manuf.* **2002**, *42*, 157–165. [CrossRef]
34. Duro, J.A.; Padget, J.A.; Bowen, C.R.; Kim, H.A.; Nassehi, A. Multi-sensor data fusion framework for CNC machining monitoring. *Mech. Syst. Signal Process.* **2016**, *66*, 505–520. [CrossRef]
35. Bryan, J. International status of thermal error research. *CIRP Ann.* **1968**, *16*, 203–215.
36. Ferreira, P.M.; Liu, C.R. A method for estimating and compensating quasistatic errors of machine tools. *J. Manuf. Sci. Eng.* **1993**, *115*, 149–159. [CrossRef]
37. Abdulshahed, A.M.; Longstaff, A.P.; Fletcher, S. The application of ANFIS prediction models for thermal error compensation on CNC machine tools. *Appl. Soft Comput.* **2015**, *27*, 158–168. [CrossRef]
38. Zhou, Z.D.; Gui, L.; Tan, Y.G.; Liu, M.Y.; Liu, Y.; Li, R.Y. Actualities and development of heavy-duty CNC machine tool thermal error monitoring technology. *Chin. J. Mech. Eng.* **2017**, *30*, 1262–1281. [CrossRef]
39. Mareš, M.; Horejš, O.; Havlík, L. Thermal error compensation of a 5-axis machine tool using indigenous temperature sensors and CNC integrated Python code validated with a machined test piece. *Precis. Eng.* **2020**, *66*, 21–30. [CrossRef]
40. Shahabi, H.H.; Ratnam, M.M. In-cycle monitoring of tool nose wear and surface roughness of turned parts using machine vision. *Int. J. Adv. Manuf. Technol.* **2009**, *40*, 1148–1157. [CrossRef]
41. Ong, P.; Lee, W.K.; Lau, R.J.H. Tool condition monitoring in CNC end milling using wavelet neural network based on machine vision. *Int. J. Adv. Manuf. Technol.* **2019**, *104*, 1369–1379. [CrossRef]
42. Chethan, Y.D.; Ravindra, H.V.; Krishne gowda, Y.T. Machined surface monitoring in turning using histogram analysis by machine vision. *Mater. Today Proc.* **2018**, *5*, 7775–7781. [CrossRef]
43. Kumar, B.M.; Ratnam, M.M. Machine vision method for non-contact measurement of surface roughness of a rotating workpiece. *Sens. Rev.* **2015**, *35*, 10–19. [CrossRef]
44. Balasundaram, M.K.; Ratnam, M.M. In-process measurement of surface roughness using machine vision with sub-pixel edge detection in finish turning. *Int. J. Precis. Eng. Manuf.* **2014**, *15*, 2239–2249. [CrossRef]
45. Joshi, K.; Patil, B. Evaluation of surface roughness by machine vision using neural networks approach. In Proceedings of the ICRAM 2019, Recent Advances in Mechanical Infrastructure, Ahmedabad, India, 20–21 April 2019.
46. Varshney, P.K. Multisensor data fusion. *Electr. Commun. Eng. J.* **1997**, *9*, 245–253. [CrossRef]
47. Hall, D.L.; Llinas, J. An introduction to multisensor data fusion. *Proc. IEEE* **1997**, *85*, 6–23. [CrossRef]
48. Kong, L.; Peng, X.; Chen, Y.; Wang, P.; Xu, M. Multi-sensor measurement and data fusion technology for manufacturing process monitoring: A literature review. *Int. J. Extrem. Manuf.* **2020**, *2*, 022001. [CrossRef]
49. Wang, H.; Li, S.; Song, L.; Cui, L. A novel convolutional neural network based fault recognition method via image fusion of multi-vibration-signals. *Comput. Ind.* **2019**, *105*, 182–190. [CrossRef]
50. Azamfar, M.; Singh, J.; Bravo-Imaz, I.; Lee, J. Multisensor data fusion for gearbox fault diagnosis using 2-D convolutional neural network and motor current signature analysis. *Mech. Syst. Signal Process.* **2020**, *144*, 106861. [CrossRef]
51. Tangjitsitharoen, S.; Rungruang, C.; Pongsathornwiwat, N. Advanced monitoring of tool wear and cutting states in CNC turning process by utilizing sensor fusion. *Adv. Mat. Res.* **2011**, *189*, 377–384. [CrossRef]
52. Garcia Plaza, E.; Nunez Lopez, P.J.; Beamud Gonzalez, E.M. Multi-sensor data fusion for real-time surface quality control in automated machining systems. *Sensors* **2018**, *18*, 4381. [CrossRef]
53. Wang, J.; Xie, J.; Zhao, R.; Zhang, L.; Duan, L. Multisensory fusion based virtual tool wear sensing for ubiquitous manufacturing. *Robot. Comput. Integr. Manuf.* **2017**, *45*, 47–58. [CrossRef]

54. Tian, Q.; Guo, S.; Melder, E.; Bian, L.; Guo, W. Deep learning-based data fusion method for in situ porosity detection in laser-based additive manufacturing. *J. Manuf. Sci. Eng.* **2021**, *143*, 041011. [\[CrossRef\]](#)
55. Safizadeh, M.S.; Latifi, S.K. Using multi-sensor data fusion for vibration fault diagnosis of rolling element bearings by accelerometer and load cell. *Inf. Fusion* **2014**, *18*, 1–8. [\[CrossRef\]](#)
56. Wei, Y.; Wu, D.; Terpenney, J. Decision-level data fusion in quality control and predictive maintenance. *IEEE Trans. Autom. Sci. Eng.* **2020**, *18*, 184–194. [\[CrossRef\]](#)
57. Xu, L.; Chen, Y.; Cui, P. Improvement of D-S evidential theory in multisensor data fusion system. In Proceedings of the Fifth World Congress on Intelligent Control and Automation, Hangzhou, China, 15–19 June 2004.
58. Liu, H.; Xia, M.; Williams, D.; Sun, J.; Yan, H. Digital twin-driven machine condition monitoring: A literature review. *J. Sens.* **2022**, *2022*, 6129995. [\[CrossRef\]](#)
59. Liu, S.; Lu, S.; Li, J.; Sun, X.; Lu, Y.; Bao, J. Machining process-oriented monitoring method based on digital twin via augmented reality. *Int. J. Adv. Manuf. Technol.* **2021**, *113*, 3491–3508. [\[CrossRef\]](#)
60. Shi, F.; Cao, H.; Wang, Y.; Feng, B.; Ding, Y. Chatter detection in high-speed milling processes based on ON-LSTM and PBT. *Int. J. Adv. Manuf. Technol.* **2020**, *111*, 3361–3378. [\[CrossRef\]](#)
61. Chang, W.Y.; Chen, C.C.; Wu, S.J. Chatter analysis and stability prediction of milling tool based on zero-order and envelope methods for real-time monitoring and compensation. *Int. J. Precis. Eng. Manuf.* **2019**, *20*, 693–700. [\[CrossRef\]](#)
62. Quintana, G.; Ciurana, J. Chatter in machining processes: A review. *Int. J. Mach. Tools Manuf.* **2011**, *51*, 363–376. [\[CrossRef\]](#)
63. Jauhari, K.; Rahman, A.Z.; Huda, M.A.; Widodo, A.; Prahasto, T. Building digital-twin virtual machining for milling chatter detection based on VMD, synchro-squeeze wavelet, and pre-trained network CNNs with vibration signals. *J. Intell. Manuf.* **2023**, *35*, 3083–3114. [\[CrossRef\]](#)
64. Bakhshandeh, P.; Mohammadi, Y.; Altintas, Y.; Bleicher, F. Digital twin assisted intelligent machining process monitoring and control. *CIRP J. Manuf. Sci. Technol.* **2024**, *49*, 180–190. [\[CrossRef\]](#)
65. Bai, L.; Zhang, J.; Yan, J.; López de Lacalle, L.N.; Muñoz, J. Cutting model integrated digital twin-based process monitoring in small-batch machining. *Int. J. Adv. Manuf. Technol.* **2025**, *136*, 109–121. [\[CrossRef\]](#)
66. Plaza, E.G.; López, P.N.; González, E.B. Efficiency of vibration signal feature extraction for surface finish monitoring in CNC machining. *J. Manuf. Process.* **2019**, *44*, 145–157. [\[CrossRef\]](#)
67. Irino, N.; Kobayashi, A.; Shinba, Y.; Kawai, K.; Spescha, D.; Wegener, K. Digital twin based accuracy compensation. *CIRP Ann.* **2023**, *72*, 345–348. [\[CrossRef\]](#)
68. Zhang, L.; Ma, C.; Liu, J. Enhancing four-axis machining center accuracy through interactive fusion of spatiotemporal graph convolutional networks and an error-controlled digital twin system. *J. Manuf. Process.* **2024**, *112*, 14–31. [\[CrossRef\]](#)
69. Zheng, Y.; Yang, H.; Jiang, G.; Hu, S.; Tao, T.; Mei, X. Data-mechanism fusion modeling and compensation for the spindle thermal error of machining center based on digital twin. *Measurement* **2025**, *250*, 117152. [\[CrossRef\]](#)
70. Luo, X.; Liu, Q.; Madathil, A.P.; Xie, W. Predictive digital twin-driven dynamic error control for slow-tool-servo ultraprecision diamond turning. *CIRP Ann.* **2024**, *73*, 377–380. [\[CrossRef\]](#)
71. Zhang, Q.; Liu, J.; Chen, X. A literature review of the digital thread: Definition, key technologies, and applications. *Systems* **2024**, *12*, 70. [\[CrossRef\]](#)
72. Lin, Z.; Zhang, Y.; Chen, C.; Guo, J.; Qi, B.; Yan, J.; Liu, Z. Multi-process digital twin closed-loop machining through shape-feature state update and error propagation knowledge graph. *Adv. Eng. Inform.* **2025**, *65*, 103403. [\[CrossRef\]](#)
73. Zhang, C.; Zhou, G.; Xu, Q.; Wei, Z.; Han, C.; Wang, Z. A digital twin defined autonomous milling process towards the online optimal control of milling deformation for thin-walled parts. *Int. J. Adv. Manuf. Technol.* **2023**, *124*, 2847–2861. [\[CrossRef\]](#)
74. Abed, M.; Gameros, A.; Mohammad, A.; Axinte, D. Swift feedback and immediate error control using a lightweight simulation approach—A case study of the digital-twin-in-the-loop for machining thin-wall structures. *J. Manuf. Syst.* **2023**, *71*, 309–322. [\[CrossRef\]](#)
75. Li, R.; Wang, S.; Wang, C.; Wang, S.; Zhou, B.; Liu, X.; Zhao, X. Research into dynamic error optimization method of impeller blade machining based on digital-twin technology. *Machines* **2023**, *11*, 697. [\[CrossRef\]](#)
76. Lu, K.; Li, Z.; Longstaff, A. In-process surface quality monitoring of the slender workpiece machining with digital twin approach. *J. Intell. Manuf.* **2025**, *36*, 2039–2053. [\[CrossRef\]](#)
77. Kim, H.; Kontar, R.A.; Okwudire, C.E. Intelligent feedrate optimization using an uncertainty-aware digital twin within a model predictive control framework. *IEEE Access.* **2024**, *12*, 49947–49961. [\[CrossRef\]](#)
78. Liu, L.; Zhang, X.; Wan, X.; Zhou, S.; Gao, Z. Digital twin-driven surface roughness prediction and process parameter adaptive optimization. *Adv. Eng. Inf.* **2022**, *51*, 101470. [\[CrossRef\]](#)
79. Zhao, Z.; Wang, S.; Wang, Z.; Wang, S.; Ma, C.; Yang, B. Surface roughness stabilization method based on digital twin-driven machining parameters self-adaption adjustment: A case study in five-axis machining. *J. Intell. Manuf.* **2022**, *33*, 943–952. [\[CrossRef\]](#)

80. Ward, R.; Sun, C.; Dominguez-Caballero, J.; Ojo, S.; Ayvar-Soberanis, S.; Curtis, D.; Ozturk, E. Machining Digital Twin using real-time model-based simulations and lookahead function for closed loop machining control. *Int. J. Adv. Manuf. Technol.* **2021**, *117*, 3615–3629. [\[CrossRef\]](#)
81. Tong, X.; Liu, Q.; Zhou, Y.; Sun, P. A digital twin-driven cutting force adaptive control approach for milling process. *J. Intell. Manuf.* **2023**, *36*, 551–568. [\[CrossRef\]](#)
82. Vishnu, V.S.; Varghese, K.G.; Gurumoorthy, B. A data-driven digital twin framework for key performance indicators in CNC machining processes. *Int. J. Comput. Integr. Manuf.* **2023**, *36*, 1823–1841. [\[CrossRef\]](#)
83. Cho, S.; Asfour, S.; Onar, A.; Kaundinya, N. Tool breakage detection using support vector machine learning in a milling process. *Int. J. Mach. Tools Manuf.* **2005**, *45*, 241–249. [\[CrossRef\]](#)
84. Sawangsri, W.; Wattanasinbumrung, P. A model approach for in-process tool condition monitoring in CNC turning using machine vision. *Int. J. Interact. Des. Manuf.* **2022**, *16*, 1439–1456. [\[CrossRef\]](#)
85. Lee, W.K.; Ratnam, M.M.; Ahmad, Z.A. Detection of chipping in ceramic cutting inserts from workpiece profile during turning using fast Fourier transform (FFT) and continuous wavelet transform (CWT). *Precis. Eng.* **2017**, *47*, 406–423. [\[CrossRef\]](#)
86. Haber, R.E.; Jiménez, J.E.; Peres, C.R.; Alique, J.R. An investigation of tool-wear monitoring in a high-speed machining process. *Sens. Actuators A Phys.* **2004**, *116*, 539–545. [\[CrossRef\]](#)
87. Qiao, Q.; Wang, J.; Ye, L.; Gao, R.X. Digital twin for machining tool condition prediction. *Procedia CIRP* **2019**, *81*, 1388–1393. [\[CrossRef\]](#)
88. Kumar, S.G.; Singh, B.K.; Kumar, R.S.; Haldorai, A. Digital twin framework for lathe tool condition monitoring in machining of aluminium 5052. *Def. Sci. J.* **2023**, *73*, 341–350. [\[CrossRef\]](#)
89. Zi, X.; Gao, S.; Xie, Y. An online monitoring method of milling cutter wear condition driven by digital twin. *Sci. Rep.* **2024**, *14*, 4956. [\[CrossRef\]](#) [\[PubMed\]](#)
90. Natarajan, S.; Thangamuthu, M.; Gnanasekaran, S.; Rakkiyannan, J. Digital twin-driven tool condition monitoring for the milling process. *Sensors* **2023**, *23*, 5431. [\[CrossRef\]](#)
91. Zhuang, K.; Shi, Z.; Sun, Y.; Gao, Z.; Wang, L. Digital twin-driven tool wear monitoring and predicting method for the turning process. *Symmetry* **2021**, *13*, 1438. [\[CrossRef\]](#)
92. Liu, Z.; Lang, Z.Q.; Gui, Y.; Zhu, Y.P.; Laalej, H. Digital twin-based anomaly detection for real-time tool condition monitoring in machining. *J. Manuf. Syst.* **2024**, *75*, 163–173. [\[CrossRef\]](#)
93. Xue, R.; Zhang, P.; Huang, Z.; Wang, J. Digital twin-driven fault diagnosis for CNC machine tool. *Int. J. Adv. Manuf. Technol.* **2024**, *131*, 5457–5470. [\[CrossRef\]](#)
94. Chen, C.; Fu, H.; Zheng, Y.; Tao, F.; Liu, Y. The advance of digital twin for predictive maintenance: The role and function of machine learning. *J. Manuf. Syst.* **2023**, *71*, 581–594. [\[CrossRef\]](#)
95. Lu, B.; Durocher, D.B.; Stemper, P. Predictive maintenance techniques. *IEEE Ind. Appl. Mag.* **2009**, *15*, 52–60. [\[CrossRef\]](#)
96. Luo, W.; Hu, T.; Ye, Y.; Zhang, C.; Wei, Y. A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin. *Robot. Comput. Integr. Manuf.* **2020**, *65*, 101974. [\[CrossRef\]](#)
97. Aivaliotis, P.; Georgoulas, K.; Chrysosolouris, G. The use of Digital Twin for predictive maintenance in manufacturing. *Int. J. Comput. Integr. Manuf.* **2019**, *32*, 1067–1080. [\[CrossRef\]](#)
98. Cao, X.; Zhao, G.; Xiao, W. Digital Twin-oriented real-time cutting simulation for intelligent computer numerical control machining. *Proc. Inst. Mech. Eng. B J. Eng. Manuf.* **2022**, *236*, 5–15. [\[CrossRef\]](#)
99. Abhilash, P.M.; Luo, X.; Liu, Q.; Madarkar, R.; Walker, C. Towards next-gen smart manufacturing systems: The explainability revolution. *NPJ Adv. Manuf.* **2024**, *1*, 8. [\[CrossRef\]](#)
100. Puthanveettil Madathil, A.; Luo, X.; Liu, Q.; Walker, C.; Madarkar, R.; Qin, Y. A review of explainable artificial intelligence in smart manufacturing. *Int. J. Prod. Res.* **2025**, *1*–44. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.