RESEARCH PROGRESS AND CHALLENGES OF DIGITAL TWIN TECHNOLOGY IN THE FIELD OF AGRICULTURAL MACHINERY TOOL WEAR

数字孪生技术在农机刀具磨损领域的研究进展及挑战

Yan-jing ZHANG, Hua ZHAN*, Jia-peng WU, Rui-jun WANG*
Chinese Academy of Agricultural Mechanization Sciences Group Co., Ltd, Beijing/China
Tel: 86-13701380963; E-mail: 13701380963@163.com;
Corresponding author: Rui-jun WANG
Tel: 86-18601289484; E-mail: zhanhua1101@163.com ;
Corresponding author: Hua ZHAN:
DOI: https://doi.org/10.35633/inmateh-77-88

Keywords: *digital twin, agricultural machinery tools, wear performance, smart agriculture, data fusion, real-time monitoring*

ABSTRACT

With the acceleration of high-performance, green, and intelligent agricultural equipment, premature wear and failure of agricultural machinery tools became a key bottleneck that restricted the high-quality development of agricultural machinery and equipment. Digital twin technology provided innovative theoretical and technical support, which enabled the accurate prediction and evaluation of the wear performance of agricultural machinery tools under dynamic and complex working conditions. This paper explained the key elements of digital twin technology and summarized the development history of tool wear research, categorizing it into three stages: physical experiment-driven, numerical simulation, and digital twin integration. Additionally, it highlighted the progress made in agricultural machinery tools based on digital twin technology, particularly in data acquisition, modeling, and data-driven approaches. The paper also introduced a case study of a self-developed agricultural machinery tool wear performance test machine. However, it addressed the key challenges faced in the application of digital twin technology for monitoring agricultural machinery tool wear, including difficulties in data perception and fusion, insufficient accuracy in multi-physical field modeling, and inadequate real-time performance. Future research focused on developing accurate multi-physics field coupling models, optimizing data processing mechanisms, and creating intelligent analysis frameworks. Additionally, it aimed to promote low-cost and efficient digital twin solutions to enhance the intelligence level and feasibility of agricultural machinery tool wear monitoring.

摘要

随着农业装备高性能、绿色化与智能化的加速推进，农机刀具过早磨损失效成为制约农机装备高质量发展的关键瓶颈。数字孪生技术为在动态复杂工况下农机刀具的磨损性能的精准预测评估提供了创新理论与技术支撑。本文阐述了数字孪生技术的关键要素，并按物理实验驱动、数值模拟和数字孪生集成 3 个阶段，总结了刀具磨损研究的发展历程；归纳了基于数字孪生技术的农机刀具在数据采集、建模和数据驱动方面的进展；具体介绍了自研农机刀具磨损性能测试试验机的案例；从数据感知与融合困难、多物理场建模精度不足以及实时性不足等方面介绍了数字孪生技术在农机刀具磨损监测应用的关键挑战。未来的研究与应用应聚焦于开发精准的多物理场耦合模型、优化数据处理机制与智能分析框架，并推广低成本高效的数字孪生解决方案，以提升农机刀具磨损监测的智能化水平和可实施性。

INTRODUCTION

As the core guarantee for sustainable social development, agricultural production faced the dual pressures of population growth and resource constraints. It urgently needed to achieve a coordinated improvement in efficiency and ecological benefits through technological innovation. The fourth industrial revolution, characterized by the deep integration of multi-source information technology, gave rise to the third agricultural green revolution—the agricultural digital revolution *(Alcácer and Cruz-Machado, 2019; Wagner et al., 2017*). This transformation promoted the evolution of agricultural production systems towards networking, digitization, and intelligence (*He et al., 2021; Upadhyay et al., 2025*). As the core component of agricultural machinery equipment, the performance of agricultural machinery tools directly affects agricultural production efficiency and cost.

Increased energy consumption and downtime losses due to tool wear accounted for over 40% of the total costs associated with the operation and maintenance of agricultural machinery. This significantly restricted the sustainable development of agriculture. At that time, tool wear management still relied on manual experience and judgment or regular mandatory replacement strategies. This approach led to issues such as conservative tool change cycles, which resulted in insufficient utilization of the tool's residual value, and a lack of system-level correlation analysis between operating environment parameters, tool conditions, and wear mechanisms (*Mohanraj et al., 2020*). Through the dynamic interaction between physical entities and virtual models, digital twins provided a full life cycle solution of "real-time perception, mechanism modeling, prediction optimization" for tool wear monitoring (*Singh et al., 2021*). Successful applications in aerospace, water conservancy, hydropower, and other industrial fields demonstrated that digital twin technology provided innovative solutions for tool wear monitoring under complex agricultural working conditions *(Madni et al., 2019; Pylianidis et al., 2021; Soori et al., 2023a; Tao et al., 2022*).

This paper discussed the current status and challenges of digital twin technology in the research of agricultural machinery tool wear. It introduced the key technologies of digital twin and its development history in the field of tool wear. The development covered three stages: physical experiment drive, numerical simulation, and digital twin integration. This paper summarized the progress of agricultural machinery tool wear data collection, modeling, and data-driven approaches based on digital twins. It also introduced the case of the self-developed agricultural machinery tool wear performance test machine. The challenges faced by digital twins in the application of agricultural machinery tool wear monitoring were discussed. Additionally, future research directions were proposed to provide a reference for the intelligent and practical application of agricultural machinery tool wear monitoring.

KEY TECHNOLOGIES OF DIGITAL TWIN

Digital twin technology achieved the digital reconstruction of the entire life cycle of the manufacturing system (*Tao et al., 2022*). It did this by constructing a dynamic interactive closed loop between physical entities and virtual space. The core technology revolved around a three-stage system of “Perception-Modeling-Decision”. The bottom layer relied on a multimodal sensor network (such as vibration, temperature, and acoustic emission sensors) to capture the operating status of physical equipment in real time and built a millisecond-level data channel. The middle platform transformed discrete monitoring data into high-fidelity virtual images based on the fusion modeling technology of deep neural networks and physical mechanisms (*Li et al., 2025b*). The upper layer realized bidirectional synchronous optimization of virtual models and physical devices through adaptive evolutionary algorithms, forming an intelligent decision-making chain based on data-driven prediction and dynamic feedback control (*Liu et al., 2023b; Su et al., 2024; Wu et al., 2021*). The technical framework broke through the limitations of traditional static simulation and single-threaded analysis *(Petri et al., 2025)*. The framework provided collaborative solutions for real-time state mapping, anomaly tracing, and life prediction in industrial scenarios such as tool wear monitoring *(Li et al., 2025a)*. The framework became the core technical foundation for the transformation of intelligent manufacturing from experience-driven to data-driven *(Leng et al., 2024; Tao et al., 2020)*.

1. Multi- domain and multi-scale fusion modeling

Multi-domain and multi-scale fusion modeling served as the core underlying technology of the digital twin system. By integrating materials, machinery, algorithms, and other multi-domain disciplines while coupling with multi-dimensional parameters, researchers constructed a high-fidelity, full life cycle virtual mapping model. This model provided theoretical support for the dynamic prediction and optimization of agricultural machinery tool wear *(Lin et al., 2026; Liu et al., 2025; Peng et al., 2025)*. Multi-domain fusion modeling emphasized the deep integration of interdisciplinary mechanisms during the conceptual design stage. Researchers built an integrated mathematical model that covered both normal working conditions and extreme loads by combining multi-disciplinary theories such as mechanical dynamics, material science, and tribology *(Jia et al., 2022)*. This approach facilitated a more comprehensive understanding of the system's behavior under various conditions. Current research mostly adopted the method of independent modeling in different fields along with data splicing *(Liu et al., 2023a)*. However, researchers encountered difficulties in eliminating the systematic errors caused by the mismatch of boundary conditions between models, especially when addressing high-dimensional nonlinear differential equations, which faced the dual constraints of computational efficiency and accuracy *(Vered and Elliott, 2023)*. Multi-scale modeling broke through the limitations of traditional one-dimensional simulation.

By utilizing the micro-macro cross-scale parameter transfer mechanism, researchers coupled and analyzed processes such as microscopic material phase changes, tool surface friction and wear, and overall machine operating efficiency *(Kumar et al., 2024)*.

2. Data driven and physical model integration

In the digital representation of agricultural machinery tool wear, the dynamic characteristics of the complex system made it difficult for traditional analytical models to independently achieve high-precision state assessment. Therefore, the deep integration of data-driven models and physical models became a key technical direction in the field of digital twins. In the field of tool wear monitoring, traditional physical models were constrained by the complexity of nonlinear mechanisms such as cutting thermal-mechanical coupling and material phase change *(Ko et al., 2015; Nouri et al., 2015)*. These constraints made it difficult to achieve accurate state inversion. Current integration strategies primarily presented two methods. A parameter adaptive correction method based on the physical equation framework *(Hao et al., 2017)* was used to achieve dynamic calibration of the cutting force model through algorithms such as Kalman filtering *(Dashan et al., 2024; Totis et al., 2020)*. Based on the hybrid decision-making architecture of Dempster-Shafer evidence theory *(Fan et al., 2025)*, the frequency domain characteristics of the vibration signal and the output of the tool wear mechanism model were fused with confidence *(Kang et al., 2020)*. The above methods improved the reliability of evaluation under normal working conditions, but there was still a problem of low accuracy between data and wear mechanism when dealing with sudden failures such as tool coating peeling.

The difficulty of the data stemmed from challenges in establishing the multi-scale relationship between multi-source heterogeneous data and the mechanism model. Additionally, there was a low dynamic correlation between wear data and process parameters throughout the life cycle. Furthermore, pure data-driven methods lacked the ability to characterize the tool microstructure evolution mechanism. *Sun et al. (2018)* adopted the approach of monitoring first and then predicting. They used a backpropagation neural network to monitor tool wear values, taking cutting parameters such as spindle speed, feed speed, and cutting depth as inputs to the monitoring model. This approach enabled the real-time acquisition of tool wear values under complex working conditions and facilitated the prediction of remaining tool life *(Soori and Arezoo, 2022)*. The development in this direction urgently required the establishment of a dual-wheel drive system that combined mechanism verification and data iteration. This system aimed to ultimately form an intelligent evaluation paradigm with physical interpretability. The construction of a distributed wear knowledge graph under the federated learning framework supported this goal.

3. Data collection and transmission

Data collection and transmission served as the core link in the construction of the digital twin system, performing the fundamental function of mapping the state of the physical world to the virtual space *(Tao et al., 2022)*. In the field of agricultural machinery tool wear monitoring, a multi-dimensional data perception network was established to capture dynamic physical field information during the tool-crop (soil) interaction process. This was achieved through the distributed deployment of multimodal sensors, including temperature, pressure, and vibration sensors *(Qu et al., 2024; Soori et al., 2023b)*. Sensor selection needed to meet three-dimensional requirements for accurately reconstructing the contact stress field in the spatial dimension. It also aimed to ensure the continuity of capturing the dynamic evolution characteristics of the agricultural machinery tool's working process in the temporal dimension. Furthermore, it was essential to guarantee the measurement accuracy of the wear characterization parameters in the quantitative dimension. The data collection and transmission system constituted the perceptual neural network of the digital twin system, and its performance directly determined the fidelity of the virtual mirror and the update time *(Vianello et al., 2023)*. In the tool wear monitoring scenario, a multimodal heterogeneous sensing network needed to be constructed. The network was designed to work with microelectromechanical system (MEMS) vibration sensors to capture cutting chatter signals, infrared thermography to track the temperature field evolution of the tool tip with resolution, and acoustic emission devices to resolve stress waves and reveal the microscopic wear state. The sensing network topology adopted a star-tree composite architecture, and time synchronization was achieved through the Time Sensitive Network (TSN) protocol to ensure the temporal and spatial alignment of multi-source data. Arshad used temperature and humidity sensors to measure environmental data and utilized the Thing Speak cloud platform for data transfer. The sensors in the greenhouse uploaded the collected data to the Thing Speak cloud. The system obtained the required temperature and humidity data from the Thing Speak API via HTTP GET requests, and the data was returned in JSON format for feedback and visualization.

At present, there were still difficulties in data collection and transmission, including distortion of feature extraction caused by signal aliasing under high-speed cutting conditions. Additionally, data loss occurred due to interference from electromagnetic and other environmental factors at industrial sites.

4. Full lifecycle data management

Full lifecycle data management was the key foundation of the digital twin, with the goal of realizing efficient data governance and value transformation *(Cooper et al., 2013; Jang et al., 2023; Sun et al., 2025)*. In whole lifecycle data management for tool wear monitoring in agricultural machinery, data collection and analysis were critical for improving tool performance and extending service life. It mainly included data from several stages. Design stage data encompassed base material and coating composition, hardness, thickness, and design parameters of the tool. Production stage data included process flow, process parameters, and quality inspection data related to tool production. Wear stage data involved environmental data such as soil type, humidity, and temperature; work parameters such as operation time, operation speed, and depth; and wear monitoring data including wear amount and wear location. Maintenance and replacement data recorded maintenance activities and tool replacements. Failure and fault analysis data encompassed analyses of failures and faults. Economic cost analysis data detailed the costs associated with tool use and maintenance. Finally, multi-source data fusion and visualization data integrated and visualized information from various sources. For the whole lifecycle data of complex systems like agricultural machinery tool wear, a distributed management architecture based on cloud servers was commonly adopted. This architecture ensured high-speed read/write capability of the data through a multi-node cooperative mechanism and provided data security by combining incremental backup with an off-site disaster recovery strategy. This architecture not only provided a highly reliable data source for intelligent parsing algorithms, but also supported key functions such as historical state tracing and the reconstruction of tool wear degradation trajectories.

5. Virtual Systems

The virtual system construction technology served as the cognitive interface of the digital twin system, focusing on the establishment of a hyper-reality mapping mechanism for the multidimensional data-physical-cognitive space *(Bevilacqua et al., 2020; Zheng et al., 2024)*. In the tool wear scenario, multi-physics field coupling modeling technology was utilized to achieve the visualization of the tool wear process. At the overall level, the dynamic process of tool wear during cutting was simulated through granular digital simulation. Using material deformation microscopic modeling, the reasons for the subtle wear of the cutting edge were analyzed. Additionally, down to the atomic level, the entire process of gradual atom exfoliation from the raw material surface was examined. The real-time rendering engine integrated ray tracing and a physics rule engine to visualize the prediction of the tool's remaining life in the virtual scene constructed on the platform *(Scheifele et al., 2019)*.

EVOLUTION OF TOOL WEAR RESEARCH TECHNOLOGY

Tool status was a key factor affecting processing quality and production efficiency. Wear and damage were the primary failure modes of tools. Tool wear or damage not only affected the surface quality and machining accuracy of the workpiece but also led to serious consequences, such as workpiece scrapping and machine downtime, posing a threat to the safe operation of the entire machining system. Research by KENNAMETAL *(Shahabi and Ratnam, 2009)*, an American company, showed that tool monitoring systems improved the utilization of the tools. Additionally, they prevented workpiece scrapping and machine tool failures caused by tool failure, leading to cost savings of up to 30%. Therefore, monitoring tool wear status was of great significance for improving product quality, reducing production costs, and enhancing production efficiency.

Traditional tool wear monitoring mainly relied on manual observation by experienced technicians or on regular tool replacement to ensure the normal operation of machine tool cutting processes. Its method required a high level of experience from personnel and demonstrated low efficiency. Additionally, replacing the tool too early or too late resulted in resource waste and reduced processing quality. With the development of intelligent manufacturing, the requirements for tool remaining life prediction technology became increasingly stringent to ensure processing quality and production safety, thereby improving production efficiency and reducing overall production costs *(Sayyad et al., 2021)*. Digital twin technology, as an advanced tool, monitored and diagnosed tool wear and breakage in real time, accurately predicting the remaining life of the tool *(Wong et al., 2020; Zhou and Xue, 2018)*. Digital twin technology dynamically managed tool status information, ensured trouble-free operation of machine tools, and promoted the advancement of intelligent manufacturing to a higher level.

1. Early stages: wear modeling based on physical experiments

The remaining life prediction method based on the wear degradation model established a functional relationship between tool wear and cutting time, cutting length, or cumulative material removal *(Wang et al., 2016)*. On this basis, the remaining life of the tool was predicted based on the tool blunting threshold and the current tool wear. *Deng et al. (2020)* proposed an analytical model of tool wear from the perspective of adhesive wear. They established the physical relationship between tool volume wear and the normal pressure in the cutting area, cutting length, and tool material hardness. This model primarily focused on a single wear mechanism and did not account for the combined effects of different wear mechanisms. This limitation resulted in insufficient universality of the model when adapting to complex cutting conditions, making it challenging to apply to all machining scenarios. *Rabinowicz et al. (1961)* established an expression for the tool wear volume rate in relation to cutting parameters from the perspective of abrasive wear. Tool wear degradation was not caused by a single wear mechanism, but resulted from the interaction of multiple wear mechanisms. *Pálmai et al. (2013)* comprehensively considered the mechanisms of abrasive wear, adhesive wear, and frictional heat generation. By analyzing the geometric characteristics of the tool and the physical wear mechanisms, they established a prediction model for the change in the wear band width of the tool flank as a function of cutting time. As the model became more complex, obtaining and calibrating parameters became increasingly difficult, which might have led to a decline in the model's predictive capability. In addition, the model may have faced issues of insufficient data and uncertainty in practical applications. *Zhang et al. (2021)* proposed a general tool wear model containing four parameters, as in (1). The model combined the logarithmic function and the power function, considering the characteristics of tool wear at different stages. It enhanced adaptability to various milling conditions and introduced a variable index x to better reflect the changing trend of tool wear over time. Although the model enhanced adaptability to different milling conditions, it still might not have fully captured the individual differences under various wear environments, particularly in terms of wear behavior with special materials or complex machining conditions.

$$w(t) = A\ln(Bt+1) + Ct^{x}\ (x>1) \tag{1}$$

Where:

$w(t)$: the functional relationship between tool wear and time t; A (μm): the fitting coefficient; B (min^{-1}): the fitting coefficient; C (μm/min^{x}): the fitting coefficient; $x\ (x>1)$: the variable indexMulti-domain.

2. Middle stage: numerical simulation and sensor technology

With the rapid development of finite element simulation technology, tool wear prediction based on numerical simulation became an important means of optimizing process parameters and extending tool life *(Wang et al., 2021)*. Additionally, simulation technology addressed the issues of individual differences and randomness present in physical experimental wear modeling. Researchers explored the complex mechanisms of tool wear using various modeling methods. *Yen et al. (2004)* utilized the commercial software DEFORM in conjunction with Usui's adhesive wear model to predict the wear on the front and rear cutting edges of the tool during orthogonal cutting. The model performs well under specific conditions; however, its focus on a single wear mechanism limits the universality of its predictions. *Xie et al. (2005)* established a tool wear prediction system using ABAQUS software, focusing on the wear of carbide tools. Although they achieved relatively good results, the prediction values still showed a significant discrepancy from the experimental values due to the overly simplified friction mechanism in the model. This indicates that relying solely on a single model may not accurately reflect the actual wear situation under complex cutting conditions. *Cappellini et al. (2022)* established a wear model for PCBN tools during the turning of AISI 52100 steel. The model dynamically updated the tool geometry based on the wear rate function, and the simulation results aligned well with the experimental findings. *Liu et al. (2020)* developed a new tool wear model for titanium alloy end milling, which allowed for the integration of various wear models into the finite element framework to predict tool wear state and morphology. Additionally, they established an empirical formula for the rapid estimation of tool life. However, this integrated approach may lead to increased complexity of the model, and its adaptability and generalization ability under certain specific conditions still need to be validated. This complexity could make the adjustment and optimization of the model parameters more challenging. *Wang et al. (2019)* established a new wear rate model and conducted finite element simulations using a specific custom subroutine to investigate the influence of machining parameters on tool wear. The results indicated that cutting speed significantly affected the life of cemented carbide tools. In terms of tool wear status monitoring, sensors played a key role in data collection and status perception. The sensors primarily used for tool wear monitoring included mechanical characteristic detection, energy parameter analysis, and acoustic signal acquisition. In actual production, the process of obtaining parameters was very complex, and there were significant differences in parameters under different materials or processing conditions, which affected the predictive accuracy of the model. Although tool wear prediction models achieved certain results in research and application, they still had many limitations. Future research focused on the integration of various wear mechanisms, the application of complex friction models, the enhancement of dynamic updating capabilities, and the fusion strategies of multiple models, in order to improve the accuracy and practicality of predictions.

The mechanical monitoring system based on cutting force and vibration signals formed a relatively complete theoretical framework. The cutting force directly reflected the edge wear state through changes in the cutting force coefficient. In contrast, vibration signals utilized the process damping effect to reveal the dynamic contact characteristics between the tool and the workpiece. *Altintas (1992)* and *Lee et al. (1995)* established a control model for the feed system. The scholars constructed the cutting force-current mapping relationship through this control model, however, they were limited by the distortion of dynamic characteristics in the signal transmission chain. *Aslan et al (2018)* used a Kalman filter to improve signal bandwidth; however, they did not consider the phase deviation caused by electromagnetic dynamic effects. *Altintas et al. (2008)* combined the workpiece surface vibration characteristics with the process damping effect and confirmed the linear correlation between the process damping coefficient and flank wear, thereby providing a new physical basis for vibration signal monitoring. The above findings revealed the time-varying influence mechanism of tool wear on the dynamic characteristics of the cutting system and achieved complementary monitoring of cutting force and vibration signals. Overall, the limitations of mechanical characteristic detection lie in its insufficient adaptability to complex dynamic environments and the issue of noise interference in signal processing.

The monitoring technology based on cutting energy consumption made significant breakthroughs. *Shi et al. (2018)* established a three-axis milling energy consumption model that integrated tool wear status, process parameters, and tool-workpiece coupling characteristics. They revealed a deterministic mapping relationship between net cutting energy consumption (total energy consumption minus idling energy consumption) and wear amount. This model improved the accuracy of energy consumption monitoring to a practical engineering level by eliminating the inherent energy consumption interference of the machine tool. It provided a new method for wear assessment under complex working conditions. However, the limitation of this model lay in its requirement for a large amount of data to support the establishment of mapping relationships. Additionally, the variation in energy consumption under different materials and cutting conditions might have been influenced by multiple factors, leading to a decrease in predictive accuracy.

Acoustic monitoring included two types of high-frequency and low-frequency signals: acoustic emission and cutting sound. Acoustic emission performed exceptionally well in micro-machining due to its high sensitivity and anti-interference ability in the frequency band above 350 kHz, while cutting sound provided an economical solution for conventional machining by extracting energy characteristics in the time-frequency domain. *Hung et al. (2013)* investigated the effects of tool wear on the frequency and amplitude of acoustic emission signals and proposed a relationship model between the acoustic emission signals during the micro-milling process and the wear of the milling cutter. *Rafezi et al. (2012)* conducted time-domain, frequency-domain, and time-frequency domain analyses of cutting sound signals and proposed a method for monitoring drill tool wear based on cutting sound. Although acoustic monitoring provided effective wear prediction data, its limitations lay in its sensitivity to external noise and the variations in signal characteristics in different processing environments, which might have affected the accuracy of the monitoring results.

With the breakthrough advancements in multi-physics field coupling modeling and dynamic signal decoupling technology, tool wear monitoring techniques underwent a transition from one-dimensional sensing to the fusion of multi-source heterogeneous data. In the future, it will be possible to achieve collaborative sensing of multi-modal signals in mechanics, electronics, and acoustics. The analysis methods will evolve from traditional time-frequency domain processing to deep learning-driven intelligent diagnosis. Moreover, engineering applications will extend beyond the ideal conditions of the laboratory to the complex working environments of industrial sites.

3. Current stage: integration of digital twin technology

Digital twin technology accurately established a tool wear model through the virtual-real interaction, mutual feedback, and iterative optimization of multi-sensor data related to the tool wear process, enabling real-time monitoring of the tool's wear condition. Through the virtual-real interaction of force-electric-acoustic multi-modal signals, a real-time comparison was made between the multi-physics coupling model of the tool-crop/soil-agricultural machine system and the measured data. By utilizing data algorithms to adjust key variables such as model parameters and boundary conditions, a digital twin of tool wear was established. *Zhao et al. (2020)* addressed the issue of multi-signal data fusion between real and virtual scenarios by proposing a hierarchical model and mapping strategy for multi-source heterogeneous data during the processing stage. This approach aimed to generate a digital twin data model that could guide real-world manufacturing processes. However, this method was potentially affected by the complexity of data acquisition and fusion in practical applications, which led to a decrease in the model's real-time performance. *Xie et al. (2021)* proposed a dual-driven data flow framework for the digital representation of various states throughout the tool lifecycle. They constructed a tool wear model that integrates physical tool wear data and virtual tool wear data, and visualized tool wear on the PC side, providing users with dynamic monitoring and recommendations for tool replacement or sharpening. Although this framework provided a good user interaction experience, its adaptability and scalability under different working conditions still needed further validation. *Zhang et al. (2023)* proposed a tool condition monitoring and comprehensive integration system model, referred to as the TCM-IPSS model, which consists of a configuration layer, equipment layer, data acquisition layer, information processing layer, and service layer. They developed a digital twin model to demonstrate the tool usage scenarios. Supported by real-time monitoring data, this model enabled the assessment of the current tool wear amount and the fitting of a wear curve to estimate the remaining tool life. However, the implementation of the model might have been affected by the data acquisition frequency and processing delays, which limited the accuracy of real-time monitoring. *Qiao et al. (2019)* proposed a data-driven digital twin model and a hybrid prediction method based on deep learning. Through the study of vibration data from milling machines, they demonstrated the accuracy of this method in predicting tool wear. However, the model's training required a large amount of high-quality data, and its predictive performance might have declined in situations where data was scarce. *Zhang et al. (2018)* proposed a model update framework based on digital twin technology, which facilitated the development of an accurate tool wear model. This framework provided valuable references for the prediction and health management of the machining process.

The above digital twin tool monitoring system made significant progress in real-time monitoring and precise modeling capabilities, improved monitoring accuracy and reliability, as well as diverse research pathways and application scenarios. However, its limitations could not be overlooked, such as the complexity of data fusion, which might have affected the model's real-time performance and accuracy; the adaptability and scalability under different operating conditions still required validation; and the demand for high-quality data restricted the model's widespread application, especially in situations where data was scarce.

In summary, the digital twin tool monitoring system mentioned above has gradually matured in terms of tool condition perception accuracy and lifespan prediction capabilities through multi-source data fusion, virtual-real closed-loop optimization, and intelligent predictive algorithms. This progress has laid a systematic technological foundation for the promotion of digital twin technology in the field of agricultural machinery tools.

RESEARCH PROGRESS AND TYPICAL APPLICATIONS IN AGRICULTURAL MACHINERY TOOL WEAR

1. *Research progress*

In recent years, digital twin technology, as an advanced information-physical fusion technology, has gradually been applied to the field of agricultural production due to its capabilities in real-time mapping, predictive analysis, and decision optimization. The wear scenarios of agricultural machinery (such as plowshares, harrow teeth, and bucket teeth) differ fundamentally from their industrial counterparts (like machine tool cutting tools and aircraft engine blades) in terms of operational objects, environments, and mechanisms of action. This necessitates significant domain adaptation for the application of digital twin technology *(Pimenov et al., 2025; Wang et al., 2024)*. Researchers in the agricultural field are exploring three technical pathways: experimental validation, numerical modeling, and data-driven approaches. They are gradually breaking through bottlenecks by leveraging multidisciplinary crossover technologies.

At the experimental validation and data acquisition level, *Mattetti et al. (2017)* deployed mechanical sensors (FlexiForce A201 and HT201) on a plow to conduct field trials. They utilized the NI CDAQ data acquisition system along with LabVIEW software to record sensor signals, tractor speed (using VBOX GPS), and load at the suspension points in real time, with a sampling frequency of 10 Hz. Their research revealed the secondary variation relationship between tillage speed and the pressure distribution on the plow wall and plow share. *Cucinotta et al. (2019)* further employed structured blue light 3D scanning technology to create three-dimensional models of the plow share after tillage. They utilized the Hausdorff method and deviation analysis to quantitatively assess the wear patterns, achieving a measurement accuracy of 0.02 millimeters for the plow share wear. This capability allows for the evaluation of the actual wear on the cutting edge. The combination of these two approaches indicates that the integration of field measurement data with high-precision scanning technology serves as a fundamental support for constructing the geometric features of the tool's digital twin. It is worth noting that, compared to the relatively controllable arrangement of measurement points in industrial environments, field environments (such as intense vibrations, dust, and uneven terrain) pose greater challenges to the stability of sensors and the quality of data collection.

In the area of numerical modeling and mechanism revelation, *Bedolla et al. (2018)* proposed a wear prediction method that combines experiments and simulations. They determined key parameters based on the spatiotemporally resolved Archard equation using ASTM G65 testing, and utilized a CFD-FEM model to simulate the interaction between circular tines and soil. Their results indicated that the relative error between the simulated wear profile and the actual measurements from 3D scanning was only 3%, confirming the numerical model's ability to capture the microscopic wear behavior of the tool's surface. However, the Archard equation and its parameter calibration methods used in this research are derived from materials tribology. When faced with the complex viscoelastic-plastic behavior of agricultural soils (such as those rich in moisture, organic matter, and clay minerals), their universality and accuracy are challenged. *Katinas et al. (2019)* addressed the wear issue of tillage tool tines by employing the Discrete Element Method (DEM) in conjunction with cone penetration resistance measurements. They discovered that the traction force in sandy clay increased by 3.9 times compared to a pure sand environment. Furthermore, the maximum difference between the simulated and actual wear loss at depths of 0-150 mm was no greater than 2.7%. This research provides a quantitative basis for wear-resistant design from the perspective of soil-tool interaction mechanisms. *Listauskas et al (2024)* utilized EDEM-Ansys simulations combined with 3D scanning comparisons to reveal the logarithmic curve pattern of wear thickness variation at the plow tip, as well as the differences from the experimental results of quadratic equations. This difference further confirmed the limitations of commonly used industrial models (such as Archard) in simulating the dynamic interactions of highly heterogeneous and multiphase media like soil and agricultural machinery. It indicated that the applicability of traditional models under complex agricultural conditions still needed improvement. These studies collectively promoted the transition of agricultural tool wear mechanisms from empirical judgment to physics-driven approaches. However, the accuracy of representing the true physical and biochemical characteristics of soil in these models still needed to be deeply optimized to address agricultural specifics.

The introduction of data-driven methods has significantly enhanced the generalization capability of models. *Cai et al. (2025)*, focusing on Mn13 bucket teeth, combined an improved Archard wear model with random forests and particle swarm optimization support vector machines. This integration improved the average R^2 value for wear depth prediction from 0.96294 to 0.98074, demonstrating the value of feature selection in decoupling complex nonlinear relationships. *Kalácska et al. (2020)* conducted a collaborative analysis using 3D optical profilometry and DEM simulation. They found that the cutting edge of tillage tines can be divided into micro-cutting and micro-plowing regions. By calculating the wear depth (D_P), they clarified the specific microscopic wear mechanisms associated with each region. Furthermore, the soil disturbance observed in the DEM simulations closely matched the wear patterns recorded during field tests, indicating a high degree of agreement in wear modes. This study revealed the unique micro-mechanisms of wear for agricultural tools, which are significantly different from the wear patterns observed in industrial tools, such as continuous cutting tools. *Hasan et al. (2022)* utilized the Hertz-Mindlin contact model and parallel bond modeling to simulate the cohesive behavior of soil. After calibrating the particle rolling friction coefficient and shear modulus through a trial-and-error method, they reduced the relative error of the soil reaction forces in the DEM simulations to within 12%. This work provides an engineering paradigm for the parameter calibration of data-driven models.

Although a certain research foundation has been established in areas such as modeling and data collection for agricultural machine tools, the biological dynamics of the operational objects (crops and soil), the variability of unstructured working environments, and the strong nonlinear characteristics of the tool-soil interaction mechanisms lead to several critical issues in the application of traditional industrial digital twins for monitoring wear in agricultural machine tools. These issues include insufficient data collection accuracy, difficulties in integrating heterogeneous data from multiple sources, and limited generalization capabilities of the models. Particularly in the full lifecycle management of agricultural tools, it is essential to design "lightweight" edge digital twins that address the strong seasonality, dispersion, and economic constraints of agricultural operations. This will facilitate online diagnostics of key wear indicators and predictions of remaining useful life. For the digital representation of wear mechanisms, it's necessary to deeply integrate multi-scale models from soil mechanics, physical chemistry, and biology, developing wear mechanism models that can characterize the potential impacts of soil biological components, such as microorganisms and root exudates. In terms of adaptive decision-making in heterogeneous scenarios, the core focus should be on constructing intelligent control strategies based on a digital twin "observe-diagnose-predict-decide" closed loop. For instance, dynamically adjusting tillage depth, speed, or replacing worn parts based on real-time wear predictions and soil condition perceptions to achieve an optimal balance between wear control, operational efficiency, and energy consumption.

2. *Typical applications*

Based on the five-dimensional model theory of digital twins proposed by Professor Tao's team *(Tao et al., 2020)*, combined with the self-developed wear performance testing machine for agricultural machinery tools (hereinafter referred to as the testing machine), a multidimensional system architecture for monitoring the wear of agricultural machine tools has been constructed (Fig. 1). This model consists of physical entities, virtual entities, a data interaction system, a service layer, and an application layer, forming a closed-loop feedback mechanism of "perception-modeling-analysis-decision". It integrates multisource data interaction, high-precision modeling, and intelligent analysis technologies, providing digital support for the performance evaluation and parameter optimization of agricultural machine tools.

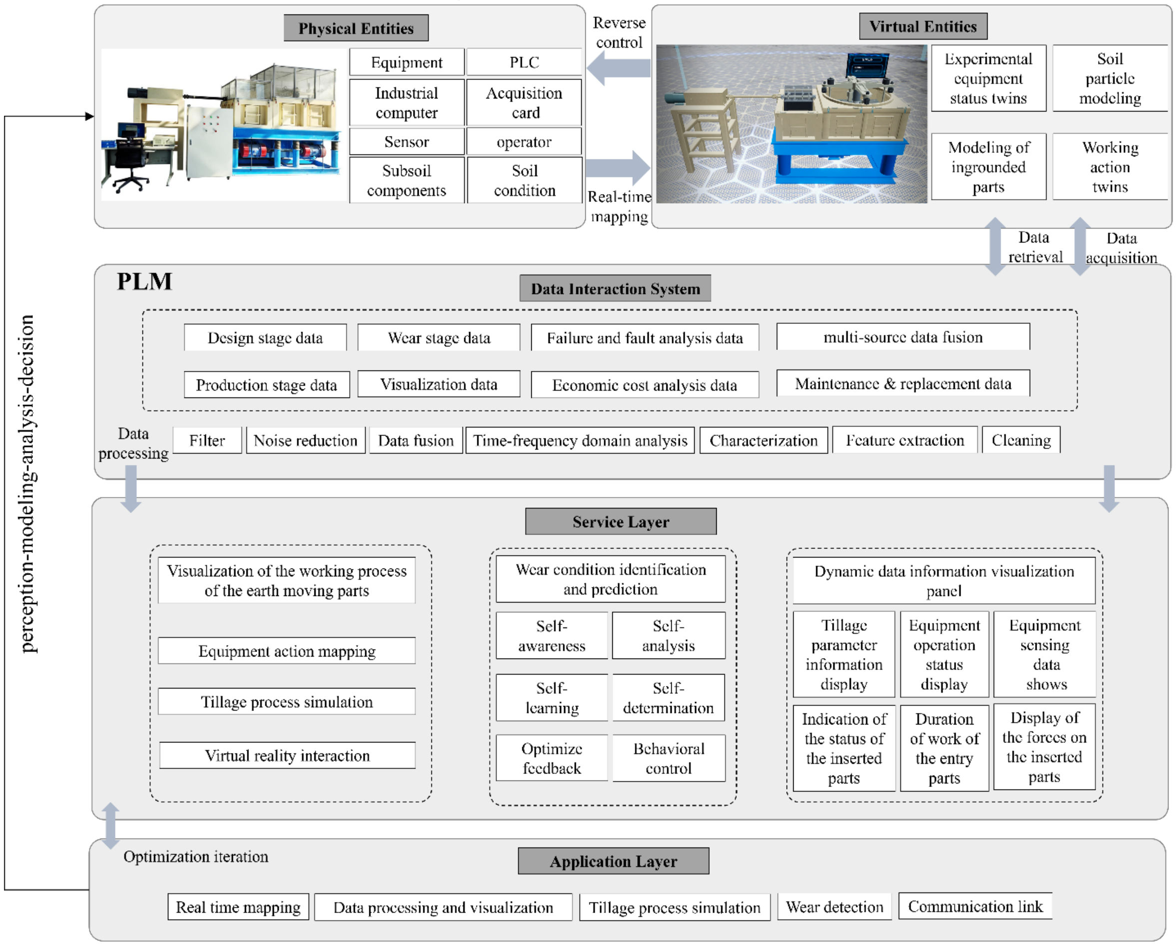

Fig. 1 - Multi-dimensional architecture for monitoring agricultural machine tool wear

2.1. Physical entity

As shown in Fig. 2, The testing machine was divided into two main functional modules based on its motion characteristics: static components (such as the base, sand box, and protective cover) and dynamic components (including the transmission shaft, rotating spindle, and cutting tools). To ensure that the digital twin model accurately reflected the real-time working conditions of the testing machine, various types of sensors (including mechanical, visual, and environmental sensors) were deployed. An embedded controller was used to perform front-end preprocessing of the sensor data. The Alta PCI5657 data acquisition system was employed to complete the time-domain alignment and noise reduction of the multi-channel signals.

Finally, the data stream was uploaded to the agricultural machinery equipment material lifecycle quality inspection system and database (referred to as the PLM system) via industrial Ethernet.

Fig. 2 - Wear performance testing machine for agricultural machinery tools

2.2. Virtual Entity

The virtual entity constructed a multi physical field coupling model. A 3D model of the testing machine was established based on Inventor, with material properties defined accordingly. The Unity3D game engine was used as the development platform. High-precision 3D models of the agricultural machinery's soil-engaging components were created using 3D modeling software, 3D MAX. By integrating technologies such as physical simulation, data analysis, and visualization, a three-dimensional digital twin system was constructed for the plowshare wear test, rotary tiller wear test, and disk harrow wear test (as shown in Fig. 3).

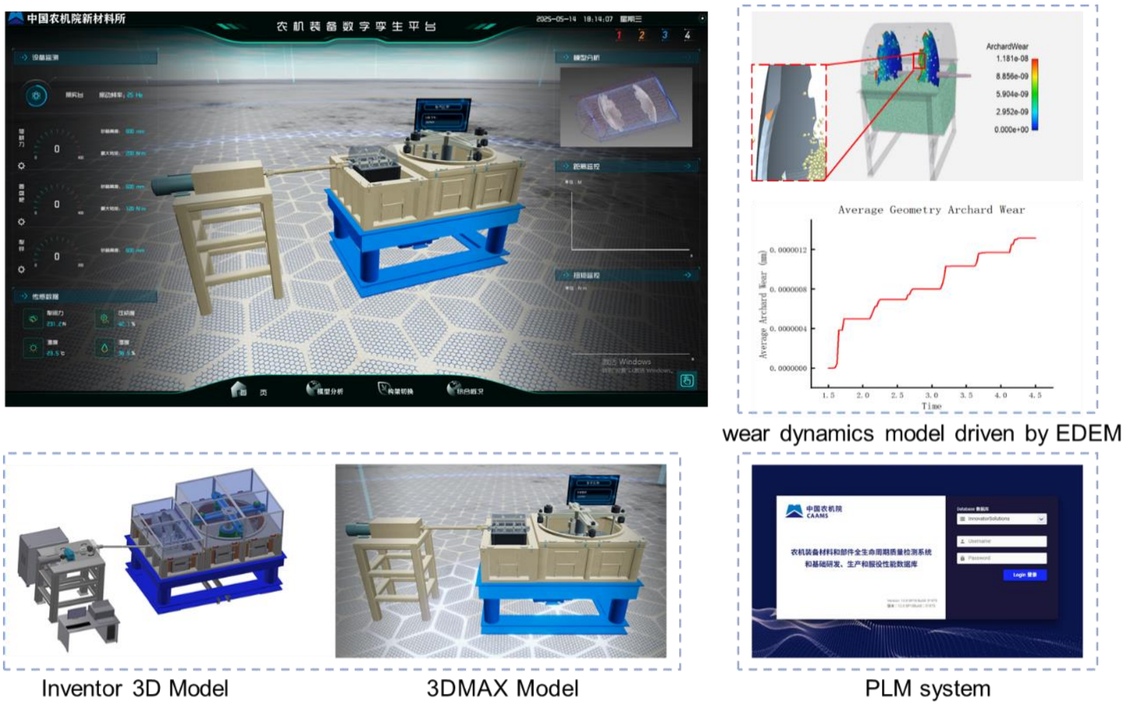

Fig. 3 -The virtual entity of the testing machine

The rigid body dynamic model was then constructed using ADAMS. To achieve accurate simulation of the tool-soil interaction behavior, a wear dynamics model driven by the Discrete Element Method (DEM) was developed. This model utilized EDEM simulation to realize multiscale predictions of cutting forces and wear depth. The virtual-physical synchronization mechanism employed the OPC UA communication protocol to enable reverse control of the physical actuators by the virtual model, thereby creating a bidirectional closed-loop virtual-physical interaction system.

2.3. Data interaction system

To ensure the real-time, efficient, and secure transmission of data within the digital twin system, a comprehensive lifecycle database for agricultural machinery tool wear was established on the Aras Innovator platform. The collected data was uploaded to the PLM system via a private cloud managed by the Chinese Academy of Agricultural Machinery Sciences. The Go programming language was utilized along with the Iris framework to establish a connection with the PLM system, enabling real-time data feedback and monitoring. The service layer integrated deep learning methods to locally construct a tool wear state prediction model. A transfer learning strategy was employed to implement edge deployment within the Iris framework, thereby enabling real-time assessment of tool wear conditions.

2.4. Service layer

By integrating the physical testing machine, virtual testing machine, and twin data, a digital twin system platform for the testing machine was established within the visualization software. This platform, oriented towards the wear testing process, achieved effects such as process visualization, transparency of tool wear conditions, and intelligent equipment management. The input layer received multisource sensor signals (including force, torque, temperature, and other data). Through a deep convolutional neural network, deep features were extracted. After optimizing network parameters and training the model, predictions of wear resistance and tool wear conditions were achieved, allowing for the analysis and assessment of the tool wear state.

2.5. Application layer

The application layer of the digital twin system for the testing machine served as an integration of physical entities, virtual entities, service platforms, twin data, and the interactions between them, which was a key factor in effectively driving the operation of the entire system. In relation to the wear testing process, twin data such as operating condition data and sensor acquisition data were retrieved and dynamically refreshed in the visualization interface. By implementing functionalities such as wear testing process simulation and tool wear prediction, it assisted operators in better understanding and analyzing the current machining conditions.

CHALLENGES

In the monitoring of wear on agricultural machine tools, the application of digital twin technology faces the following challenges: (1) The agricultural operating environment was characterized by strong vibrations, high dust levels, and electromagnetic interference, which led to high noise levels and low reliability of sensor data. Furthermore, there were significant temporal and spatial scale differences in multimodal data (such as stress, temperature, and soil composition), and the real-time synchronization and feature correlation algorithms were not yet mature, which restricted the input accuracy of the twin model. (2) Tool wear involved cross-scale interactions among mechanical, thermal, material, and soil factors. Existing simulation models simplified the mathematical description of contact nonlinearity and the wear mechanisms of heterogeneous materials, resulting in accumulated discrepancies between the dynamic responses of the twin model and the actual tool. Consequently, the reliability of long-term monitoring decreased. (3) The bandwidth of field networks was limited, making it difficult for traditional cloud-based twin architectures to meet the millisecond-level response requirements. Lightweight model compression resulted in a loss of predictive accuracy, while high-fidelity models exceeded the computational capacity of embedded systems in agricultural machinery, thereby restricting the implementation of online closed-loop control.

CONCLUSION AND OUTLOOK

This paper primarily explored the research status and challenges of digital twin technology in the monitoring of agricultural machine tool wear. It systematically reviewed the key technologies of digital twins, the technological evolution in the field of tool wear, the current state of research and application cases of agricultural machine tool wear monitoring based on digital twin technology, and the challenges faced in this area. Digital twin technology has achieved certain successes in data collection, simulation modeling, and data-driven approaches for monitoring agricultural machine tool wear. However, it still faced multiple challenges in practical applications, including issues related to the accuracy of signal acquisition, the complexity of data processing, and the real-time performance of models. The integrated application of digital twin technology provided robust technical support for the intelligent transformation of the agricultural machinery industry, laying the foundation for the comprehensive lifecycle management and performance optimization of tools. This advancement facilitated the shift from experience-driven approaches to data-driven methodologies.

Future research can be conducted in the following directions: (1) Improve the data reliability of sensors under complex working conditions by designing and manufacturing sensors capable of operating in environments with strong vibrations, high dust levels, and electromagnetic interference, thereby enhancing the accuracy and reliability of data collection. Additionally, establish an intelligent analysis framework based on deep learning to improve the accuracy of data acquisition and processing. In particular, when dealing with complex conditions, soil heterogeneity, and dynamic system changes, it is necessary to develop more flexible models. (2) Develop more precise multi-physics coupling models that take into account the interactions between mechanics, thermodynamics, materials, and crops (soil), in order to enhance the accuracy of tool wear models. Additionally, investigate more complex nonlinear contact models that consider the wear behavior of heterogeneous materials, aiming to reduce the discrepancies between the responses of the digital twin and the actual tools. (3) In the deployment of agricultural machine tool wear monitoring systems, it is essential to balance system cost and performance issues, particularly among small-scale users such as farmers. Promoting low-cost and efficient digital twin solutions can help reduce implementation barriers.

ACKNOWLEDGEMENT

This research was funded by National Key R&D Program of China (No.: 2024YFB3714100) and the State-owned Capital Fund: Digital Life System of Agricultural Machinery Equipment-Wear Performance Test of Entering Earth Parts.

REFERENCES

[1] Alcácer, V., &Cruz-Machado, V. (2019). Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing Systems. *Engineering Science and Technology, an International Journal,* 22, 899-919.https://doi.org/10.1016/j.jestch.2019.01.006

[2] Altintas, Y. (1992). Prediction of Cutting Forces and Tool Breakage in Milling from Feed Drive Current Measurements. *Journal of Engineering for Industry,* 114, 386-392.https://doi.org/10.1115/1.2900688

[3] Altintas, Y., Eynian, M., &Onozuka, H. (2008). Identification of dynamic cutting force coefficients and chatter stability with process damping. *CIRP Annals,* 57, 371-374.https://doi.org/10.1016/j.cirp.2008.03.048

[4] Aslan, D., &Altintas, Y. (2018). Prediction of Cutting Forces in Five-Axis Milling Using Feed Drive Current Measurements. *IEEE/ASME Trans. Mechatron.,* 23, 833-844.10.1109/TMECH.2018.2804859

[5] Bedolla, P. O., Vorlaufer, G., Rechberger, C., Bianchi, D., Eder, S. J., Polak, R., &Pauschitz, A. (2018). Combined experimental and numerical simulation of abrasive wear and its application to a tillage machine component. *Tribology International,* 127, 122-128.https://doi.org/10.1016/j.triboint.2018.03.019

[6] Bevilacqua, M., Bottani, E., Ciarapica, F. E., Costantino, F., Di Donato, L., Ferraro, A., Mazzuto, G., Monteriù, A., Nardini, G., Ortenzi, M., Paroncini, M., Pirozzi, M., Prist, M., Quatrini, E., Tronci, M., &Vignali, G. (2020). Digital Twin Reference Model Development to Prevent Operators' Risk in Process Plants. *Sustainability,* 12, 1088.https://doi.org/10.3390/su12031088

[7] Cai, Z., Yan, J., Qiao, Y., Li, R., Shi, Y., Zhang, J., &Zhang, Z. (2025). Impact wear behavior of austenitic steel bucket teeth based on machine learning. *Journal of Materials Research and Technology,* 36, 6128-6141.https://doi.org/10.1016/j.jmrt.2025.04.258

[8] Cappellini, C., &Abeni, A. (2022). Development and implementation of crater and flank tool wear model for hard turning simulations. *The International Journal of Advanced Manufacturing Technology,* 120, 2055-2073.https://doi.org/10.1007/s00170-022-08885-y

[9] Cooper, J., Noon, M., Jones, C., Kahn, E., &Arbuckle, P. (2013). Big Data in Life Cycle Assessment. *Journal of Industrial Ecology,* 17, 796-799.https://doi.org/10.1111/jiec.12069

[10] Cucinotta, F., Scappaticci, L., Sfravara, F., Morelli, F., Mariani, F., Varani, M., &Mattetti, M. (2019). On the morphology of the abrasive wear on ploughshares by means of 3D scanning. *Biosystems Engineering,* 179, 117-125.https://doi.org/10.1016/j.biosystemseng.2019.01.006

[11] Dashan, Z., Yuntian, C., &Shiyi, C. (2024). Filtered partial differential equations: a robust surrogate constraint in physics-informed deep learning framework. *Journal of Fluid Mechanics,* 999, A40-A40.https://doi.org/10.1017/jfm.2024.471

[12] Deng, B., Peng, F., Zhou, L., Wang, H., Yang, M., &Yan, R. (2020). A comprehensive study on flank wear progression of polycrystalline diamond micro-tool during micro end-milling of SiCp/Al composites. *Wear,* 456-457, 203291.https://doi.org/10.1016/j.wear.2020.203291
[13] Fan, N., Liu, J., Ye, L., Pan, Z., Dai, Y., &Fan, W. (2025). Dempster–Shafer evidence theory based IFA detection approach towards mixed attacks in VNDN. *Computers & Industrial Engineering,* 204, 111084.https://doi.org/10.1016/j.cie.2025.111084
[14] Hao, L., Bian, L., Gebraeel, N., &Shi, J. (2017). Residual Life Prediction of Multistage Manufacturing Processes With Interaction Between Tool Wear and Product Quality Degradation. *IEEE Transactions on Automation Science and Engineering,* 14, 1211-1224.https://doi.org/10.1109/TASE.2015.2513208
[15] Hasan, H. S., Abbas, H., Ali, E., Gholamhossein, S., &Alireza, B. (2022). Development of a dual sideway-share subsurface tillage implement: Part 1. Modeling tool interaction with soil using DEM. *Soil and Tillage Research,* 215, 105201.https://doi.org/10.1016/j.still.2021.105201
[16] He, D., Lu, C., Tong, Z., Zhong, G., &Ma, X. (2021). Research Progress of Minimal Tillage Method and Machine in China. *AgriEngineering,* 3, 633-647.https://doi.org/10.3390/agriengineering3030041
[17] Hung, C.-W., &Lu, M.-C. (2013). Model development for tool wear effect on AE signal generation in micromilling. *The International Journal of Advanced Manufacturing Technology,* 66, 1845-1858.https://doi.org/10.1007/s00170-012-4464-x
[18] Jang, S., Jeong, J., Lee, J., &Choi, S. (2023). Digital Twin for Intelligent Network: Data Lifecycle, Digital Replication, and AI-Based Optimizations. *IEEE Communications Magazine,* 61, 96-102.https://doi.org/10.1109/MCOM.001.2200837
[19] Jia, W., Wang, W., &Zhang, Z. (2022). From simple digital twin to complex digital twin Part I: A novel modeling method for multi-scale and multi-scenario digital twin. *Advanced Engineering Informatics,* 53, 101706.https://doi.org/10.1016/j.aei.2022.101706
[20] Kalácska, Á., Baets, P. D., Fauconnier, D., Schramm, F., Frerichs, L., &Sukumaran, J. (2020). Abrasive wear behaviour of 27MnB5 steel used in agricultural tines. *Wear,* 442-443, 203107-203107.https://doi.org/10.1016/j.wear.2019.203107
[21] Kang, M., Zhang, L., &Tang, W. (2020). Modeling of the Distribution of Undeformed Chip Thickness Based on the Real Interference Depth of the Active Abrasive Grain. *IEEE Access,* 8, 101628-101647.https://doi.org/10.1109/ACCESS.2020.2994072
[22] Katinas, E., Chotěborský, R., Linda, M., &Jankauskas, V. (2019). Wear modelling of soil ripper tine in sand and sandy clay by discrete element method. *Biosystems Engineering,* 188, 305-319.https://doi.org/10.1016/j.biosystemseng.2019.10.022
[23] Ko, D.-C., Kim, S.-G., &Kim, B.-M. (2015). Influence of microstructure on galling resistance of cold-work tool steels with different chemical compositions when sliding against ultra-high-strength steel sheets under dry condition. *Wear,* 338-339, 362-371.https://doi.org/10.1016/j.wear.2015.07.014
[24] Kumar, K., Sarkar, J., &Mondal, S. S. (2024). Multi-scale-multi-domain simulation of novel microchannel-integrated cylindrical Li-ion battery thermal management: Nanoparticle shape effect. *Journal of Energy Storage,* 84, 110824.https://doi.org/10.1016/j.est.2024.110824
[25] Lee, J. M., Choi, D. K., Kim, J., &Chu, C. N. (1995). Real-Time Tool Breakage Monitoring for NC Milling Process. *CIRP Annals,* 44, 59-62.https://doi.org/10.1016/S0007-8506(07)62275-6
[26] Leng, J., Guo, J., Xie, J., Zhou, X., Liu, A., Gu, X., Mourtzis, D., Qi, Q., Liu, Q., Shen, W., &Wang, L. (2024). Review of manufacturing system design in the interplay of Industry 4.0 and Industry 5.0 (Part I): Design thinking and modeling methods. *Journal of Manufacturing Systems,* 76, 158-187.https://doi.org/10.1016/j.jmsy.2024.07.012
[27] Li, Q., Zhao, G., Li, J., Li, S., Yan, W., Tian, X., &Ai, S. (2025a). An in-situ predictive method for modulus degradation in composite structures with fatigue damage: Applications in digital twin technology. *Mechanical Systems and Signal Processing,* 237, 113090.https://doi.org/10.1016/j.ymssp.2025.113090
[28] Li, Y., Li, Z., Ren, J., Du, W., &Shen, W. (2025b). A high-accuracy deep learning framework for digital twin model development of actual chemical processes. *Engineering Applications of Artificial Intelligence,* 159, 111780.https://doi.org/10.1016/j.engappai.2025.111780
[29] Lin, Y.-H., Chiang, C.-H., Yu, C.-M., &Huang, J. Y.-T. (2026). Intelligent docking control of autonomous underwater vehicles using deep reinforcement learning and a digital twin system. *Expert Systems with Applications,* 296, 129085.https://doi.org/10.1016/j.eswa.2025.129085

[30] Listauskas, J., Jankauskas, V., Žunda, A., Katinas, E., &Gargasas, J. (2024). Estimation and modelling the wear resistance of plough points and knife coulters by discrete element method. *Wear,* 556-557, 205508.https://doi.org/10.1016/j.wear.2024.205508
[31] Liu, J., Ma, C., Gui, H., &Wang, S. (2023a). Intelligent digital-twin prediction and reverse control system architecture for thermal errors enabled by deep learning and cloud-edge computing. *Expert Systems with Applications,* 225, 120122.https://doi.org/10.1016/j.eswa.2023.120122
[32] Liu, X., Jiang, D., Tao, B., Xiang, F., Jiang, G., Sun, Y., Kong, J., &Li, G. (2023b). A systematic review of digital twin about physical entities, virtual models, twin data, and applications. *Advanced Engineering Informatics,* 55, 101876.https://doi.org/10.1016/j.aei.2023.101876
[33] Liu, Y., Shen, H., Zhao, G., Du, X., &Jing, X. (2025). Digital twin-based assembly process framework utilizing STEP and knowledge graph. *Advanced Engineering Informatics,* 67, 103502.https://doi.org/10.1016/j.aei.2025.103502
[34] Liu, Z., Yue, C., Li, X., Liu, X., Liang, S. Y., &Wang, L. (2020). Research on Tool Wear Based on 3D FEM Simulation for Milling Process. *Materials and Manufacturing Processes,* 4, 121.https://doi.org/10.3390/jmmp4040121
[35] Madni, A., Madni, C., &Lucero, S. (2019). Leveraging Digital Twin Technology in Model-Based Systems Engineering. *Systems,* 7, 7.https://doi.org/10.3390/systems7010007
[36] Mattetti, M., Varani, M., Molari, G., &Morelli, F. (2017). Influence of the speed on soil-pressure over a plough. *Biosystems Engineering,* 156, 136-147.https://doi.org/10.1016/j.biosystemseng.2017.01.009
[37] Mohanraj, T., Shankar, S., Rajasekar, R., Sakthivel, N. R., &Pramanik, A. (2020). Tool condition monitoring techniques in milling process — a review. *Journal of Materials Research and Technology,* 9, 1032-1042.https://doi.org/10.1016/j.jmrt.2019.10.031
[38] Nouri, M., Fussell, B. K., Ziniti, B. L., &Linder, E. (2015). Real-time tool wear monitoring in milling using a cutting condition independent method. *International Journal of Machine Tools and Manufacture,* 89, 1-13.https://doi.org/10.1016/j.ijmachtools.2014.10.011
[39] Pálmai, Z. (2013). Proposal for a new theoretical model of the cutting tool's flank wear. *Wear,* 303, 437-445.https://doi.org/10.1016/j.wear.2013.03.025
[40] Peng, X., Jiang, R., Yuan, Z., Zhang, A., Chen, Z., Wang, D., Chen, X., &Zhang, Y. (2025). A sensor-integrated digital twin framework for molten pool monitoring of laser powder bed fusion. *Computers in Industry,* 171, 104332.https://doi.org/10.1016/j.compind.2025.104332
[41] Petri, I., Amin, A., Ghoroghi, A., Hodorog, A., &Rezgui, Y. (2025). Digital twins for dynamic life cycle assessment in the built environment. *Science of The Total Environment,* 993, 179930.https://doi.org/10.1016/j.scitotenv.2025.179930
[42] Pimenov, D. Y., Silva, L. R. R. d., Kuntoğlu, M., Abrão, B. S., Paes, L. E. D. S., &Linul, E. (2025). Review of advanced sensor system applications in grinding operations. *Journal of Advanced Research*. https://doi.org/10.1016/j.jare.2025.01.013.https://doi.org/10.1016/j.jare.2025.01.013
[43] Pylianidis, C., Osinga, S., &Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. *Computers and Electronics in Agriculture,* 184, 105942.https://doi.org/10.1016/j.compag.2020.105942
[44] Qiao, Q., Wang, J., Ye, L., &Gao, R. X. (2019). Digital Twin for Machining Tool Condition Prediction. *Procedia CIRP,* 81, 1388-1393.https://doi.org/10.1016/j.procir.2019.04.049
[45] Qu, S., Cui, J., Cao, Z., Qiao, Y., Men, X., &Fu, Y. (2024). Position Estimation Method for Small Drones Based on the Fusion of Multisource, Multimodal Data and Digital Twins. *Electronics,* 13, 2218.https://doi.org/10.3390/electronics13112218
[46] Rabinowicz, E., Dunn, L. A., &Russell, P. G. (1961). A study of abrasive wear under three-body conditions. *Wear,* 4, 345-355.https://doi.org/10.1016/0043-1648(61)90002-3
[47] Rafezi, H., Behzad, M., &Akbari, J. (2012). Time Domain and Frequency Spectrum Analysis of Sound Signal for Drill Wear Detection. *International Journal of Electrical and Computer Engineering,* 4, 722-725.
[48] Sayyad, S., Kumar, S., Bongale, A., Kamat, P., Patil, S., &Kotecha, K. (2021). Data-Driven Remaining Useful Life Estimation for Milling Process: Sensors, Algorithms, Datasets, and Future Directions. *IEEE Access,* 9, 110255-110286.https://doi.org/10.1109/ACCESS.2021.3101284
[49] Scheifele, C., Verl, A., &Riedel, O. (2019). Real-time co-simulation for the virtual commissioning of production systems. *Procedia CIRP,* 79, 397-402.https://doi.org/10.1016/j.procir.2019.02.104

[50] Shahabi, H. H., &Ratnam, M. M. (2009). In-cycle monitoring of tool nose wear and surface roughness of turned parts using machine vision. *The International Journal of Advanced Manufacturing Technology,* 40, 1148-1157.https://doi.org/10.1007/s00170-008-1430-8
[51] Shi, K. N., Zhang, D. H., Liu, N., Wang, S. B., Ren, J. X., &Wang, S. L. (2018). A novel energy consumption model for milling process considering tool wear progression. *Journal of Cleaner Production,* 184, 152-159.https://doi.org/10.1016/j.jclepro.2018.02.239
[52] Singh, M., Fuenmayor, E., Hinchy, E. P., Qiao, Y., Murray, N., &Devine, D. (2021). Digital twin: Origin to future. *Applied System Innovation,* 4, 36.https://doi.org/10.3390/asi4020036
[53] Soori, M., &Arezoo, B. (2022). Cutting tool wear prediction in machining operations, a review. *Journal of New Technology and Materials,* 12, 15-26.https://hal.science/hal-03888252v1
[54] Soori, M., Arezoo, B., &Dastres, R. (2023a). Digital twin for smart manufacturing, A review. *Sustainable Manufacturing and Service Economics,* 2, 100017.https://doi.org/10.1016/j.smse.2023.100017
[55] Soori, M., Arezoo, B., &Dastres, R. (2023b). Internet of things for smart factories in industry 4.0, a review. *Internet of Things and Cyber-Physical Systems,* 3, 192-204.https://doi.org/10.1016/j.iotcps.2023.04.006
[56] Su, S., Nassehi, A., Qi, Q., &Hicks, B. (2024). A methodology for information modelling and analysis of manufacturing processes for digital twins. *Robotics and Computer-Integrated Manufacturing,* 90, 102813.https://doi.org/10.1016/j.rcim.2024.102813
[57] Sun, H., Cao, D., Zhao, Z., &Kang, X. (2018). A Hybrid Approach to Cutting Tool Remaining Useful Life Prediction Based on the Wiener Process. *IEEE Transactions on Reliability,* 67, 1294-1303.https://doi.org/10.1109/TR.2018.2831256
[58] Sun, X., Zhang, F., Wang, J., Yang, Z., Huang, Z., &Xue, R. (2025). Digital twin for smart manufacturing equipment: modeling and applications. *The International Journal of Advanced Manufacturing Technology,* 137, 4929-4946.https://doi.org/10.1007/s00170-025-15468-0
[59] Tao, F., Liu, A., Hu, T., &Nee, A., 2020. Digital twin driven smart design. Academic Press.
[60] Tao, F., Xiao, B., Qi, Q., Cheng, J., &Ji, P. (2022). Digital twin modeling. *Journal of Manufacturing Systems,* 64, 372-389.https://doi.org/10.1016/j.jmsy.2022.06.015
[61] Totis, G., Dombovari, Z., &Sortino, M. (2020). Upgraded Kalman Filtering of Cutting Forces in Milling. *Sensors,* 20, 5397.https://doi.org/10.3390/s20185397
[62] Upadhyay, G., Raheman, H., &Dubey, R. (2025). Regression Models and Multi-Objective Optimization Using the Genetic Algorithm Technique for an Integrated Tillage Implement. *AgriEngineering,* 7, 121.https://doi.org/10.3390/agriengineering7040121
[63] Vered, Y., &Elliott, S. J. (2023). The use of digital twins to remotely update feedback controllers for the motion control of nonlinear dynamic systems. *Mechanical Systems and Signal Processing,* 185, 109770.https://doi.org/10.1016/j.ymssp.2022.109770
[64] Vianello, P. I. A., Abrão, A. M., Maia, A. A. T., &Pereira, I. C. (2023). Tool Life Monitoring in End Milling of AISI H13 Hot Work Die Steel Using a Low-Cost Vibration Sensor Connected to a Wireless System. *Experimental Techniques,* 47, 1149-1159.https://doi.org/10.1007/s40799-022-00619-9
[65] Wagner, T., Herrmann, C., &Thiede, S. (2017). Industry 4.0 Impacts on Lean Production Systems. *Procedia CIRP,* 63, 125-131.https://doi.org/10.1016/j.procir.2017.02.041
[66] Wang, B., Liu, Z., Cai, Y., Luo, X., Ma, H., Song, Q., &Xiong, Z. (2021). Advancements in material removal mechanism and surface integrity of high speed metal cutting: A review. *International Journal of Machine Tools and Manufacture,* 166, 103744.https://doi.org/10.1016/j.ijmachtools.2021.103744
[67] Wang, C., Ming, W., &Chen, M. (2016). Milling tool's flank wear prediction by temperature dependent wear mechanism determination when machining Inconel 182 overlays. *Tribology International,* 104, 140-156.https://doi.org/10.1016/j.triboint.2016.08.036
[68] Wang, W., Liu, W., Zhang, Y., Liu, Y., Zhang, P., &Jia, Z. (2024). Precise measurement of geometric and physical quantities in cutting tools inspection and condition monitoring: A review. *Chinese Journal of Aeronautics,* 37, 23-53.https://doi.org/10.1016/j.cja.2023.08.011
[69] Wang, Y., Su, H., Dai, J., &Yang, S. (2019). A novel finite element method for the wear analysis of cemented carbide tool during high speed cutting Ti6Al4V process. *The International Journal of Advanced Manufacturing Technology,* 103, 2795-2807.https://doi.org/10.1007/s00170-019-03776-1
[70] Wong, S. Y., Chuah, J. H., &Yap, H. J. (2020). Technical data-driven tool condition monitoring challenges for CNC milling: a review. *The International Journal of Advanced Manufacturing Technology,* 107, 4837-4857.https://doi.org/10.1007/500170-020-05303-2

[71] Wu, C., Zhou, Y., Pereia Pessôa, M. V., Peng, Q., &Tan, R. (2021). Conceptual digital twin modeling based on an integrated five-dimensional framework and TRIZ function model. *Journal of Manufacturing Systems,* 58, 79-93.https://doi.org/10.1016/j.jmsy.2020.07.006

[72] Xie, L. J., Schmidt, J., Schmidt, C., &Biesinger, F. (2005). 2D FEM estimate of tool wear in turning operation. *Wear,* 258, 1479-1490.https://doi.org/10.1016/j.wear.2004.11.004

[73] Xie, Y., Lian, K., Liu, Q., Zhang, C., &Liu, H. (2021). Digital twin for cutting tool: Modeling, application and service strategy. *Journal of Manufacturing Systems,* 58, 305-312.https://doi.org/10.1016/j.jmsy.2020.08.007

[74] Yen, Y.-C., Söhner, J., Lilly, B., &Altan, T. (2004). Estimation of tool wear in orthogonal cutting using the finite element analysis. *Journal of Materials Processing Technology,* 146, 82-91.https://doi.org/10.1016/S0924-0136(03)00847-1

[75] Zhang, G., &Sun, H. (2018). Enabling cutting tool services based on in-process machining condition monitoring. *Internationaljournal ofInternet Manufacturing and Services,* 5, 51-66.https://doi.org/10.1504/IJIMS.2018.090590

[76] Zhang, H., Qi, Q., Ji, W., &Tao, F. (2023). An update method for digital twin multi-dimension models. *Robotics and Computer-Integrated Manufacturing,* 80, 102481.https://doi.org/10.1016/j.rcim.2022.102481

[77] Zhang, Y., Zhu, K., Duan, X., &Li, S. (2021). Tool wear estimation and life prognostics in milling: Model extension and generalization. *Mechanical Systems and Signal Processing,* 155, 107617.https://doi.org/10.1016/j.ymssp.2021.107617

[78] Zhao, P., Liu, J., Jing, X., Tang, M., Sheng, S., Zhou, H., &Liu, X. (2020). The Modeling and Using Strategy for the Digital Twin in Process Planning. *IEEE Access,* 8, 41229-41245.https://doi.org/10.1109/ACCESS.2020.2974241

[79] Zheng, H., Liu, T., Liu, J., &Bao, J. (2024). Visual analytics for digital twins: a conceptual framework and case study. *Journal of Intelligent Manufacturing,* 35, 1671-1686.https://doi.org/10.1007/s10845-023-02135-y

[80] Zhou, Y., &Xue, W. (2018). Review of tool condition monitoring methods in milling processes. *The International Journal of Advanced Manufacturing Technology,* 96, 2509-2523.https://dol.org/10.1007/500170-018-1768-5