Research on the Application of Intelligent Manufacturing in Machining

Pinqing Wang

College of Mechanical Engineering, Tianjin University of Science and Technology, Tianjin, 300457, China

w1790544142@mail.tust.edu.cn

Abstract. Under the background of intelligent transformation of global manufacturing industry, traditional machining industry urgently needs to respond to the challenges of efficiency, precision and flexible production through technological innovation. This paper systematically researches the synergistic enabling mechanism of core technologies such as Industrial Internet of Things (IIoT), Artificial Intelligence (AI), and Digital Twin, and proposes a phased implementation path from equipment interconnection, to single-point optimization, and then to system synergy. Based on empirical cases in aerospace and automotive manufacturing, the economic value of intelligent processing optimization, predictive maintenance and flexible production is verified. Aiming at the problem of data security and talent gap, a distributed data sharing framework based on blockchain and a joint training model between industry, academia, and research are proposed. The study shows that the deep integration of 5G and edge computing will promote machining to the higher-order intelligence stage of adaptive decision-making and cloud-edge collaboration, which provides systematic methodology support for the intelligent transformation of small and medium-sized enterprises (SMEs). This paper provides a theoretical framework and practical reference for the transformation and upgrading of machining enterprises, with both academic value and engineering guidance.

INTRODUCTION

With the rapid development of social and economic development and the continuous progress of science and technology, the traditional machining industry is facing more severe market competition, the global manufacturing industry is accelerating the intelligent transformation, Germany's Industry 4.0 through the digital twin technology to realize the virtual debugging, shorten the debugging cycle; U.S. “advanced national manufacturing strategy” focuses on leading the future of intelligent manufacturing The U.S. “Advanced National Manufacturing Strategy” focuses on leading the future of intelligent manufacturing, developing innovative materials and processing technologies, and expanding and enriching the talent pool of advanced manufacturing; Japan takes high-precision CNC machine tool technology as the core, and the five-axis linkage machining has high precision and small processing errors.

Since China first put forward the “Made in China 2025” strategy in 2014, intelligent manufacturing has been developing rapidly under the drive of policies, and the market scale of industrial robots has jumped to the first place in the world, but the rate of autonomy of high-end equipment needs to be improved urgently. 2023 China's intelligent testing equipment industry market size of 243.66 billion yuan, an increase of 7.9% over the previous year, and by 2025 the overall industry scale of the market is expected to exceed 300 billion yuan [1]. But the traditional machining industry is still facing serious challenges: such as the utilization rate of ordinary CNC machine tools is not high, there is room for improvement in the rate of numerical control; aero-engine blade machining due to thermal deformation of the error is large, although it is micron level but it may lead to catastrophic consequences, especially turbine blades, thermal deformation error if not strictly controlled may cause Engine failure, precision is limited [2]; enterprise multi-species orders there is a longer time-consuming change of type, and small batch enterprises in the production planning needs to consider the lack of equipment sharing, mold change line time and other flexibility issues, there is a challenge to meet the demand for customization.

The introduction of intelligent manufacturing technology provides a systematic solution for the machining industry. Firstly, through real-time monitoring and compensation technology, tool life prediction model based on acoustic emission sensors with high compensation accuracy; then through predictive maintenance, multi-modal data fusion such as vibration, temperature and current, so that unplanned downtime can be reduced; also through rapid changeover, for example, Genetic Algorithm (GA) to optimize the changeover sequence, and the time-consuming can be compressed in a shorter period of time.

The aim of this paper is to systematically build a framework for the application of smart manufacturing technologies in machining. This paper focuses on the synergistic mechanism of industrial IoT, artificial intelligence and digital twin, and proposes a phased implementation path. The economic benefits of intelligent machining optimization and flexible production are quantified through empirical cases in aerospace and automotive manufacturing. In view of the barriers to data integration and talent gaps, the paper proposes localized solutions such as “industry-university-research joint laboratories” and “industry-level data security standards”. This paper analyzes the key technology system of intelligent manufacturing, verifies the logic of technological empowerment through typical scenarios, evaluates the practical value in combination with industry cases, and puts forward strategies to cope with challenges and future research directions. Through the multi-dimensional linkage of “technology-scene-industry”, it provides systematic methodological support for the intelligent transformation of China's machining industry.

KEY TECHNOLOGIES OF INTELLIGENT MANUFACTURING

Core Technology Systems

Industrial Internet of Things (IIoT)

The Industrial Internet of Things, i.e. through the advent of miniature low-cost sensors and high-bandwidth wireless networks, means that even the smallest devices can be connected today as long as they have some level of digital intelligence. They can be monitored and tracked, their status data shared and communicated with other devices. All this data can then also be collected and analyzed to improve the efficiency of business processes. The technical principle is based on 5G, edge computing and the OPC UA protocol to interconnect devices and interoperate data. For example, the Siemens Sinumerik ONE CNC system, which collects data points and analyzes parameters such as spindle temperature and vibration spectrum in real time to achieve tool life prediction and failure warning [3].

The core functions of IIoT include equipment status monitoring (spindle temperature, vibration spectrum, tool life); data standardization based on the OPC UA protocol and ISO 23247 standards, building a unified framework for machine tool data interaction and reducing the complexity of cross-platform integration [4].

Artificial Intelligence (AI)

AI can carry out process optimization, which can be based on its own work situation in a timely manner Analysis, judgment, feedback and processing, at the same time, according to the results of the processing, to carry out reasonable adjustments and control, and then be able to obtain a higher quality processing solution. For example, from the algorithm of reinforcement learning to optimize cutting parameters, particle swarm algorithm (PSO) optimization Inconel 718 milling parameters, effectively reducing tool wear rate [5]. And AI can be defect detection, for example, by using the YOLOv7 model to identify complex texture surface defects, the leakage rate is very low, more real-time, can be based on edge computing, so that the detection delay <50ms to meet the production line beat demand [6]. Process knowledge modeling based on C-A-R diagram, knowledge management, support for intelligent matching of the feature processing chain. For example, a baking company in Hunan optimizes the baking temperature control curve through AI algorithms, resulting in a significant reduction in the standard deviation of the water content of potato chips and a reduction in energy consumption [7].

Digital Twin

Digital Twin is mainly based on computer technology as the main application, with the help of specialized graphic processing software, the manufacturing process of machining, and product simulation, so that operators and technicians can have a visually accurate understanding of the real machining process, so as to achieve the purpose of reducing the defective rate. The technical architecture of the digital twin is divided into three levels, the physical layer: sensor network acquisition of machine tools, workpieces, and environmental data; the virtual layer: ANSYS Twin Builder to build a high-fidelity simulation model; interaction layer: real-time data-driven virtual model iteration [8]. Application scenarios of digital twin: virtual debugging, based on RoboDK platform 3D model and PLC intermodulation, the debugging cycle is greatly shortened; deformation prediction, can be simulated through the software milling deformation of aerospace aluminum alloy thin-walled parts, so that the error is controlled in a very small range [9]; collaborative decision-making, gas turbine blade belt grinding, six-axis linkage parameter dynamic adjustment to make surface roughness reduction [10].

Technology Empowerment Logic

The enabling logic of intelligent manufacturing for the machining industry is essentially to reconfigure the production process through the closed loop of data-model-decision making, realizing the paradigm leap from experience-driven to data-driven, from reactive response to proactive prediction, and from single-machine silo to system collaboration. Data-driven can replace the traditional parameter-setting mode that relies on workers' experience. Traditional modes such as setting cutting parameters through technicians' experience can lead to parameter conservatization, such as choosing parameters lower than the optimal value in order to avoid tool breakage, which can lead to loss of efficiency, as well as fluctuations in parameters that may be due to the technician's individual differences [11].

Proactive prediction can be shifted from post-failure maintenance to health state prediction through intelligent prediction techniques, such as multimodal data fusion through a variety of data such as vibration, temperature, current, etc.; and then the use of detection algorithms to diagnose the type of failure, such as convolutional neural networks to determine the wear of the spindle bearings [12]; at the same time, life can be predicted through the remaining useful life (RUL) prediction model based on the Weibull distribution to carry out life Prediction [7].

Collaborative optimization is reflected in the dynamic resource scheduling across equipment and processes. Traditional independent machine tools cannot share data, which leads to resource waste and scheduling lag; intelligent collaborative technology is applied to different scenarios through the type of algorithms to achieve the effect of optimization goals, such as genetic algorithms (GA) for multi-species and small batch production to achieve the purpose of minimizing the time of changeover [7].

APPLICATION SCENARIOS OF INTELLIGENT MANUFACTURING

Intelligent Machining Optimization

The first is reflected in the real-time compensation of tool wear. The technical principle of real-time compensation is to realize a series of processes through data acquisition, model construction, and closed-loop control. Based on the LSTM network to predict the remaining life of the tool, the precision error is more accurate, and the CNC system automatically adjusts the tool bias value to reduce the machining dimensional deviation. For example, Ningde Times New Energy Intelligent Manufacturing Demonstration Plant introduces an adaptive laser welding control system to dynamically compensate for thermal deformation, which improves the yield of battery modules and reduces the production labor per GWh [13]. It can be seen that the real-time compensation of tool wear can improve product quality while reducing the cost of wear and tear.

The second is reflected in the vibration suppression and surface quality control. The technology path is divided into active damping control, such as piezoelectric actuator real-time inhibition of thin-walled parts processing vibration, so that the amplitude is reduced; and for the optimization of process parameters, such as based on genetic algorithms to solve the optimal combination of cutting parameters, such as feed, speed, depth of cut[7]. Specific case results such as Lockheed Martin through the vibration suppression technology will be thin-walled surface roughness Ra significantly reduced so that the qualification rate increased [14]. Huagong laser optical waveguide glass intelligent production line integrated LCO laser crack orientation technology and three-axis precision positioning system, to achieve glass wafer cutting accuracy and processing efficiency is higher, compared with the traditional Bessel cutting technology, the strength of the product to improve at the same time reduces the proliferation of micro-cracks [15]. The above cases are sufficient to reflect the vibration and surface quality control can greatly improve the product qualification rate and quality strength.

Predictive Maintenance

The first can be used in machine tool spindle health management, through the vibration acceleration sensor to capture the abnormal frequency, infrared thermography to monitor the temperature trend of multi-modal data fusion, and fusion through the CNN model to diagnose the type of failure, with high accuracy [12]; based on the Weibull distribution model can predict the remaining life of the bearings, in advance for early warning of failure [16]. Predictive maintenance of machine tool spindle health can greatly enhance the service life of machine tools.

Secondly, the application of industrial IoT can be reflected in the state monitoring of process equipment, such as the OPC UA protocol to achieve equipment data interoperability, real-time collection of spindle power, vibration spectrum and other parameters; General Electric (GE) aviation plant through IIoT monitoring of 300+ units of equipment, so that the utilization rate has been improved. A baking enterprise in Hunan adopts OPC UA protocol to open up ERP, MES and WMS systems, and the response time of order scheduling is shortened [7]. The above cases reflect that through the detection of the state of process equipment, equipment utilization can be significantly improved, thus increasing production efficiency.

Flexible Manufacturing Cells

The quick changeover system firstly reflects flexible production, and the quick changeover system has both hardware integration and software support, such as the combination of zero-point positioning fixture and AGV automatic handling equipment; the MES system dynamically dispatches resources and simulates the changeover process by combining with digital twins [16]. A bakery enterprise in Hunan realizes the whole process automation of the production line by deploying an AGV logistics system and machine vision quality inspection equipment [7]. The intelligent production line of Huagong Laser's optical waveguide glass adopts AGV automatic transportation and an intelligent sorting system to work together, greatly shortening the changeover time and greatly increasing the production capacity so that the production efficiency is greatly improved [15].

Secondly, it can reflect flexible production through dynamic scheduling and mixed line production, respond to multi-species order scheduling through optimization algorithms and genetic algorithms and respond to emergency order insertion through reinforcement learning, and simulate different scheduling schemes through virtual production lines, select the scheme with the lowest energy consumption or the fastest delivery to synchronize to the physical production line, and realize the collaboration of digital twins.

Closed-Loop Quality Control

Closed-loop quality control first lies in online monitoring and error compensation, such as laser scanners to obtain the size of the workpiece, combined with the digital twin model prediction of thermal deformation error, and then through the CNC system to correct the tool path, such as aircraft engine blade contour error control, so as to realize the reverse compensation [2]. Ningde Times New Energy Intelligent Manufacturing Demonstration Plant realizes high precision cutting of pole pieces and high pass rate of welding airtightness through multimodal data fusion, such as real-time collection of temperature, pressure, vibration spectrum and other parameters [15]. The entire production process mobilizes multimodal data to strictly control the quality and significantly improve the product qualification rate.

Secondly, it is embodied in the automatic sorting of vision-guided, specific technology to realize such as the YOLOv7 model to identify surface defects, such as scratches, air holes, etc., with high detection accuracy [6]; industrial robots combined with the vision system to realize automatic sorting. Vision-guided automatic sorting is extremely accurate and product quality monitoring is guaranteed.

CHALLENGES AND FUTURE DIRECTIONS

Challenge Analysis

Although intelligent manufacturing technology shows significant potential in the machining field, its implementation still faces multiple challenges.

First, there are barriers to technical integration, such as heterogeneous equipment data interoperability relying on OPC UA, MTConnect and other protocols conversion, resulting in increased system complexity; industrial AI models in the generalization of cross-working scenarios still need to be improved, such as AI application system has not yet been standardized, the integration and analysis of cross-system data face technical barriers, data-driven AI models may encounter the “seen” working conditions, and so on. The data-driven AI model may encounter “unseen” working conditions [14].

Secondly, there are limitations to economic feasibility, the cost of intelligent transformation of small and medium-sized enterprises, capital, talent, technology and other aspects of the relative lack of high digital empowerment costs, including the cost of data governance and system integration; long return on investment cycle, some enterprises due to the pressure of short-term revenue to give up the depth of the transformation, and only use local automation [1,7].

Finally, there is still a gap between the supply and demand of talents who need to master CNC machining, data science and control theory at the same time, and the mechanism for cooperation between industry, academia and research is not yet mature.

Future Outlook

The evolution of intelligent manufacturing in the machining field will show three major trends:

The first is the deep integration of technology, the distributed edge computing framework based on blockchain will control the delay extreme compression, support high dynamic scenes, such as aerospace thin-walled parts vibration suppression [14]; Augmented Reality (AR) technology Microsoft HoloLens to achieve the natural interaction between the worker and the intelligent device, to realize the human-computer mingling, reduce the Training costs, enhance maintenance efficiency improvement.

Then there is a cloud manufacturing ecosystem driven by model innovation, such as Shenyang Machine Tools i5 platform in 2023 through the “machine tool as a service” model, to achieve the processing capacity on-demand call; through the remanufacturing technology, such as laser cladding repair of the old mold materials, so that the utilization rate of the resources to improve [15].

The most important thing is to have a sustainable development orientation, adhere to green manufacturing, such as intelligent machine tools through energy efficiency optimization to reduce energy consumption, and reduce carbon emissions intensity; based on the digital twin life cycle management (PLM) system, to achieve parts and components remanufacturing rate increase [17].

CONCLUSION

The paper examines the application of smart manufacturing technologies in the machining industry, exploring how technologies such as the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), and Digital Twins work together. By analyzing how these technologies work together, the research shows that they have the ability to change the way machining processes are executed, leading to more accurate machining and more flexible production. Key findings suggest that closed-loop “data-model-decision” systems play an important role in shifting production from being experience-based to being more data-dependent. Several examples from industries such as aerospace and automotive show that smart manufacturing can lead to good economics. This paper proposes a framework that moves from mere device connectivity to single-point optimization to system-level collaboration, thus providing a path forward that small and medium-sized enterprises can learn from. Despite these advances, challenges remain. For example, algorithms are not robust enough in harsh conditions, and the lack of proper data-sharing systems between different companies remains a barrier. Future research needs to look at improving the ability of AI to interpret data using a combination of physical and data models. Data security standards also need to be developed to facilitate cross-industry collaboration. In addition, the use of technologies such as blockchain, edge computing, and augmented reality (AR) can help bridge the gap between human-computer interaction and also accelerate the process of creating more sustainable production practices. This study not only delves into the technological aspects of smart manufacturing but also proposes practical solutions that are specifically applicable to China's machining industry. By ensuring that technological advances match industry needs, this work lays the groundwork for improving the global competitiveness of the precision manufacturing industry, while also addressing key challenges such as talent development and resource optimization.

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