

Application and prospect of AI in the non-standard equipment industry

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Abstract: With the advancement of the Industry 4.0 wave, artificial intelligence (AI) technology is profoundly reshaping the entire industrial chain of the machining industry. As "customized solutions" in the industrial field, non-standard mechanical equipment, characterized by complex design and high production flexibility requirements, is deeply coupled with AI technology. In 2023, the global industrial AI market size exceeded \$40 billion, with the non-standard equipment sector accounting for 27%, marking that AI technology has evolved from an auxiliary tool to a core driving force in this industry. This article systematically explores the full-process application of AI in non-standard mechanical equipment, from product design to operation and maintenance services, focusing on analyzing technological breakthroughs and industrial value in core aspects such as intelligent design, intelligent process planning, intelligent machining and quality control, intelligent supply chain optimization, warehouse logistics revolution, intelligent assembly and debugging, predictive maintenance, and the integration of intelligence and the Internet of Things.

Key words: intelligent design; revolution in warehousing and logistics; intelligent assembly and debugging; predictive maintenance; integration of intelligence and the Internet of Things

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As the cornerstone of the modern industrial system, the international significance of the machinery industry is primarily manifested in its profound restructuring of the global industrial chain. As a capital-intensive and technology-intensive industry, machinery equipment manufacturing is directly linked to the national economic lifelines such as energy, transportation, and construction. National strategies like Germany's Industry 4.0 and China's Made in China 2025 prioritize its development. In the context of accelerated restructuring of the global production network, the international significance of the machinery industry is further reflected in its strategic support for global industrial security. Non-standard machinery drives the transformation of manufacturing from standardized production to flexibility and intelligence through customized solutions, while AI technology is reshaping the value chain of the non-standard equipment industry, demonstrating technological breakthroughs and industrial value in core aspects such as intelligent design, intelligent process planning, processing

and quality control, intelligent optimization of supply chains, revolution in warehousing and logistics, intelligent assembly and debugging, predictive maintenance, and the integration of intelligence and the Internet of Things.

1 Intelligent design

In terms of theoretical foundation application, AI can handle data from multiple disciplines such as mechanical engineering, materials science, and thermodynamics simultaneously, achieving more systematic and comprehensive optimization of design compared to manual methods. By reconstructing the theoretical system of mechanical design through a knowledge graph, the AI course "Mechanical Principles and Mechanical Design" from Beihang University achieves intelligent integration of theoretical teaching and

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engineering practice through a graph of 190 core knowledge points.

By optimizing the design process through intelligent algorithms, the development cycle of non-standard equipment has been shortened by over 30%. In rapidly iterative fields such as 3C electronics and new energy, AI-driven modular design systems (such as the Mecmesin meviy platform) have achieved a 40% increase in production line switching efficiency.

AI, through topology optimization algorithms and interdisciplinary knowledge fusion, can enhance material utilization by 15% to 30% while ensuring strength. For instance, in a robotic arm design case, AI generated 10 innovative structural schemes, resulting in a market share 15% higher than that of competing products. By combining vision/force sensors with natural language processing, real-time environmental adjustments to motion paths can be achieved, avoiding structural interference and equipment operational collisions while enhancing efficiency. AI can recommend optimal combinations based on a material performance database, integrating parameters such as mechanical properties, corrosion resistance, and cost. Traditional material selection relies on engineer experience, often overlooking the potential applications of new materials. AI technology, by integrating cross-domain databases, has established a multidimensional correlation model of material performance, processing technology, and cost-effectiveness. The Materials Project platform in the United States has included electronic structure data for over 150,000 materials, supporting intelligent screening. Meanwhile, generative AI is driving reverse innovation in material design. AI automates reliability and durability assessments by learning and analyzing physical property test data of materials. For instance, random forest and XGBoost algorithms can effectively handle multi-objective optimization problems in material selection. By setting target performance parameters, the composition of materials that meet requirements can be deduced in reverse.

By combining AI with finite element analysis, it is possible to quickly predict the stress distribution of mechanical structures under complex loads, such as simultaneously evaluating aerodynamics and material properties in turbine blade design. Through fluid mechanics simulations and vibration analysis, potential fatigue failure risks can be

identified in advance.

AI can automatically complete standardized tasks such as standard part selection and dimensioning based on system data, shortening the design cycle of standard components and reducing the error rate of drawings through real-time interference checking. Its parameter optimization capability can handle hundreds of design variables simultaneously, quickly finding the optimal balance point between performance, cost, reliability, and other objectives. Through reinforcement learning algorithms, AI can simultaneously balance conflicting objectives such as strength, cost, and manufacturability, enhancing material utilization for complex structural components. Currently, AI has formed a closed-loop design process from concept generation to verification, with its core value lying in breaking through the limitations of human experience and achieving a dual leap in design efficiency and accuracy. For example, in intelligent auxiliary design, rubber machinery equipment company Saixiang Technology applies force analysis of 3D design software combined with model materials and mechanical performance parameters to automatically and quickly analyze structural model optimization design. The topology optimization algorithm can automatically generate mechanical structures that are lighter than those designed manually. At the same time, through standardized and modular design, the product design cycle is shortened, reducing the number of scheme modifications.

2 Intelligent process planning, machining, and quality control

AI analyzes mechanical manufacturing data through the Six Sigma process management method to achieve dynamic optimization of process parameters. In the field of CNC machining, AI-driven quality control systems can reduce the defect rate by 50% by detecting deviations that are difficult for the human eye to identify through real-time analysis of sensor data. AI algorithms automatically generate optimal tool paths, increasing production efficiency by 20% and making machine tool availability management more efficient. The deep reinforcement learning-controlled CNC system can automatically compensate parameters based on tool wear status, enabling a mold company to increase processing efficiency by 40%. It also extends tool life by adjusting cutting parameters

in real time through the controller. AI simultaneously analyzes machine tool parameters, processing parameters, and workpiece quality data to establish precise mathematical models, enabling automatic adjustment of processing parameters and automatic control of machine tools, thereby improving process stability. During production, AI precisely controls reaction conditions to reduce energy consumption.

Computer vision-based surface defect detection systems, such as Cognex ViDi, can achieve real-time detection with μm -level accuracy. As a result, a bearing company reduced its scrap rate from 1.2% to 0.15%. Foxconn's intelligent quality inspection system achieves product surface defect detection through image analysis, with an accuracy rate exceeding 99%. Smart manufacturing systems can automatically adjust production line parameters, enabling intelligent optimization of the production process.

3 Intelligent optimization of supply chain and revolution in warehousing and logistics

AI analyzes historical sales data, market trends, and seasonal fluctuations through deep learning algorithms to achieve accurate demand forecasting. For example, Saixiang Technology utilizes a digital project management platform to dynamically monitor the status of all projects and analyze data models in a timely manner. This enables it to predict commodity demand several months in advance, guiding procurement and production planning. This technology can reduce raw material inventory backlog, while also lowering the risk of stockouts and reducing dead stock. Additionally, based on a multi-dimensional supplier evaluation system, it enhances the efficiency of procurement decision-making. The constructed capacity model can analyze equipment status and order changes in real-time, and improve delivery achievement rates through an intelligent production scheduling system.

A domestic tire factory has improved equipment utilization and shortened order delivery cycles through the intelligent scheduling function of the MES system. The MES system integrates an SPC control module, effectively reducing the product defect rate. The MES system can seamlessly integrate with AGV logistics vehicles, achieving full-process automation from raw material warehousing to finished product

off-line. At the same time, the digital twin factory optimizes energy usage patterns through AI, reducing energy-related emissions.

AI agents can generate a "road, rail, and water storage" multimodal transport solution that balances cost and timeliness, reducing logistics and warehousing costs. By leveraging blockchain and IoT technology, the entire supply chain can be made transparent, and AI can switch to backup suppliers in minutes in the event of geopolitical or natural disasters.

4 Intelligent assembly and debugging

Through virtual assembly technology (see Figure 1), Saixiang Technology has reduced on-site assembly issues by 50% during the design phase. Based on data, a digital twin model of the equipment is constructed, and AI simulates the installation process in a virtual environment, enabling early detection of issues such as mechanical interference and electrical conflicts. Through virtual debugging, the physical debugging cycle has been compressed from 20 days to 15 days.



Figure 1 Virtual assembly

A certain automobile company deploys a sensor network (such as torque sensors and visual inspection equipment) on the assembly line to collect data in real-time, including bolt tightening torque and component positioning accuracy. This data is then transmitted to the cloud via a 5G/TSN network. Over 2,000 sensors are installed on the final assembly line, processing data at a rate of gigabytes per second, ensuring synchronous updates between the virtual model and the physical production line.

A robotics company restores the geometry and motion logic of equipment such as robotic arms and AGVs through 3D scanning and CAD modeling, achieving an accuracy of $\pm 0.1 \text{ mm}$. Meanwhile, the virtual model predicts assembly

anomalies (such as bolt missing with an accuracy of 92%) through AI algorithms and automatically issues adjustment instructions to the physical equipment, forming a "perception-analysis-execution" closed loop.

5 Predictive maintenance

AI integrates sensor data such as vibration, temperature, and current, and identifies early fault characteristics such as bearing wear and gear cracks through time series analysis (e.g., LSTM model). An unsupervised learning model based on an autoencoder can automatically detect data anomalies, and the AI warning system can reduce maintenance costs and unplanned downtime. At the same time, AI algorithms (such as random forest) analyze historical maintenance data and dynamically adjust maintenance cycles. For example, tire factories use the IoT platform developed by Saixiang

Technology to timely assess equipment operating status based on monitored equipment parameters (see Figure 2) and sensor alarm information (see Figure 3), directly carrying out targeted maintenance and shortening equipment troubleshooting and downtime.

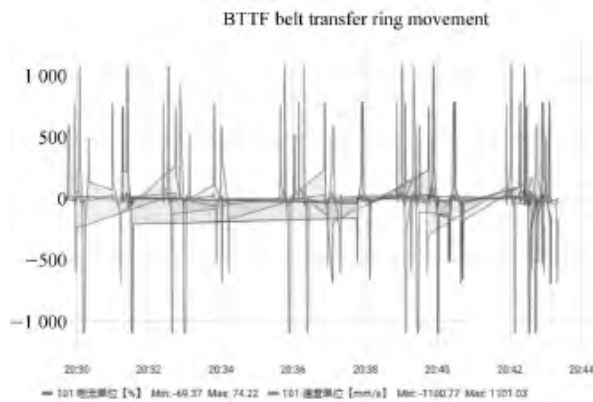


Figure 2 Equipment parameters

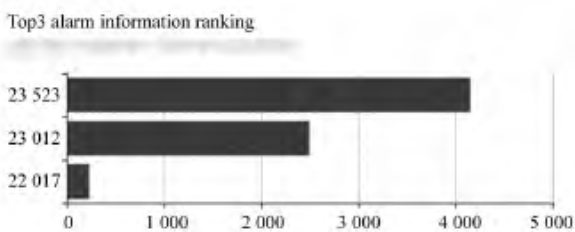
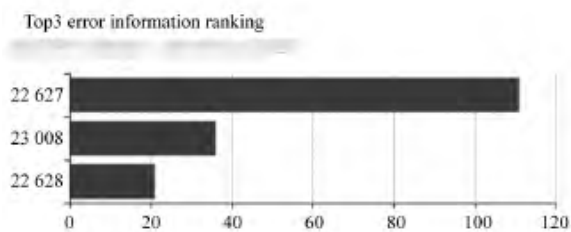


Figure 3 Equipment alarm information

6 Integration of intelligence and the Internet of Things

The integration of AI and the Internet of Things (IoT) has given birth to new business models, enabling industrial Internet platforms to achieve device interconnectivity and endowing devices with autonomous decision-making capabilities. For instance, in flexible production lines, AI integrates multiple variables to intelligently regulate the operational status of equipment, thereby reducing equipment operation and production costs. Machine vision is used to automatically detect product defects, enhancing the yield rate. For example, Saixiang Technology simulates multi-device collaboration through the IoT platform (see Figure 4) and optimizes takt time (see Figure 5). By integrating logistics, energy, and other information, the IoT platform detects inventory dynamics and energy consumption fluctuations.



Figure 4 Equipment collaboration

Cycle time of each workstation				
	Calculation cycle: OK			
Workstation	Current	Best	Average	Output production
 Carcass	157.0. (157.00 min)	102. (102.00 min)	138.5. (138.50 min)	519
 Belt	93.0. (93.00 min)	90. (90.00 min)	121.1. (121.10 min)	524
 Molding	128.0. (128.00 min)	105. (105.00 min)	136.8. (136.80 min)	520

Figure 5 Equipment operation cycle

Smart factories utilize AI for comprehensive optimization and management, replacing traditional single-point intelligent devices. AI excels in energy conservation and carbon reduction. For instance, steel enterprises have optimized the blast furnace ironmaking process through AI, resulting in a 10% reduction in energy consumption and a 15% decrease in carbon emissions.

However, AI still has certain limitations in the non-standard equipment industry. For example, AI faces the dilemma of small sample learning, and the characteristic of single-piece/small-batch production of non-standard equipment leads to insufficient training data, resulting in a high false alarm rate in rare defect detection by AI models. At the same time, AI has difficulty handling the unique process coupling relationships of non-standard equipment. In traditional processes, parameter adjustment relies on worker experience, and such knowledge is difficult to inherit through data modeling. AI systems cannot replace the "hand feel judgment" of experienced workers in certain specific assembly areas, such as precision adjustment relying on worker intuition in assembly, where such tacit knowledge is difficult to quantify by algorithms. Additionally, although AI can generate

topological optimization schemes, it lacks grasp of subjective factors such as aesthetics and ergonomics. Generative design performs well in the 3C electronics field, but it is prone to "over-optimization" in heavy industry scenarios, leading to decreased manufacturability. Meanwhile, the data gap between equipment management requirements and end-effector data remains unresolved, which are all reasons why AI cannot be widely applied in the non-standard equipment industry for the time being.

7 Summary

AI technology is reshaping the value chain of non-standard mechanical equipment, evolving from single-point intelligence to system intelligence. In the future, key technologies such as small-sample learning and causal reasoning need to be prioritized to build a full-chain intelligent ecosystem encompassing "design-manufacturing-service". AI-driven non-standard equipment will gradually occupy a larger share of the high-end market and become the core carrier of intelligent manufacturing.

