A Review of Research on the optimization of the Entire Life Cycle of Mechanical Manufacturing Based on Artificial Intelligence: from Design to Operation and Maintenance

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Abstract:With the deepening of Industry 4.0, the integration of artificial intelligence technology and the mechanical manufacturing industry has become the core driving force for promoting industrial upgrading. This article takes the entire life cycle of mechanical manufacturing as the research object, and systematically reviews the application and optimization achievements of artificial intelligence in various stages of design, manufacturing, and operation. By analyzing the innovative applications of AI technologies such as genetic algorithms and neural networks in the design phase, the practice of integrating intelligent manufacturing systems with industrial big data in the manufacturing phase, and breakthroughs in intelligent fault diagnosis and predictive maintenance in the operation and maintenance phase, the key role of AI technology in improving manufacturing efficiency, reducing costs, and enhancing reliability has been revealed. Provide theoretical and practical references for the intelligent transformation of the mechanical manufacturing industry.

Keywords: Artificial Intelligence; Mechanical Manufacturing; Full Lifecycle; Design Optimization; Intelligent Manufacturing; It Operation Management

1.Introduction

1.1 Research Background and Significance

As a pillar industry of the national economy, the development level of the mechanical manufacturing industry is directly related to the country's industrialization process and comprehensive national strength. In the context of increasingly fierce global industrial competition, traditional mechanical manufacturing models face bottlenecks such as low efficiency, resource waste, and insufficient innovation, and urgently need to achieve transformation and upgrading through technological innovation. The rapid development of artificial intelligence technology has provided a new paradigm for optimizing the entire life cycle of mechanical manufacturing. Its abilities such as self-learning, intelligent decision-making, and accurate prediction can run through the entire process of product design, processing and manufacturing, operation and maintenance services, and even scrapping and recycling, promoting the transformation of manufacturing mode from "experience driven" to "data-driven".

From a practical perspective, the deep integration of artificial intelligence and mechanical manufacturing can not only significantly improve production efficiency - according to the International Federation of Robotics (IFR) data, the introduction of AI optimized intelligent production lines can increase production efficiency by more than 30%, but also reduce energy and raw material consumption through precise regulation, helping to achieve the "dual carbon" goal. Meanwhile, AI based predictive maintenance can reduce equipment downtime by 50%, significantly improving the economy and reliability of the entire product lifecycle. Therefore, the systematic review of the application achievements and optimization paths of artificial intelligence in the entire life cycle of mechanical manufacturing has important theoretical and practical value for promoting industry technological innovation and enhancing industry competitiveness.

1.2 Current Research Status at Home and Abroad

The research on artificial intelligence in the field of mechanical manufacturing started earlier in foreign countries, and the application of expert systems in process planning began to be explored in the 1990s. In recent years, manufacturing powerhouses such as the United States and Germany have promoted the deep penetration of AI technology throughout its entire lifecycle through initiatives such as the "Advanced Manufacturing Leadership Strategy" and "Industry 4.0". For example, the digital twin platform developed by Siemens AG in Germany has achieved real-time mapping of product design and manufacturing processes, and its quality inspection system based on deep learning has an accuracy rate of 99.8%; General Electric's (GE) Predix platform utilizes AI algorithms to analyze operational data of aircraft engines, enabling the commercial application of predictive maintenance.

Although domestic research started relatively late, it has developed rapidly. In the design phase, teams from universities such as Tsinghua University and Shanghai Jiao Tong University have made breakthroughs in optimizing complex mechanical structures based on genetic algorithms, and the related achievements have been applied to the design of key components for high-speed rail; During the manufacturing phase, the smart factory built by Huawei in collaboration with Foxconn has reduced production pace by 20% through an AI scheduling system; In the field of operation and maintenance, Sany Heavy Industry's "Root Cloud" platform utilizes AI to diagnose engineering machinery faults, increasing response speed by 60%. However, comparative analysis shows that there are still problems with fragmented technology and insufficient cross stage collaboration in domestic research, especially in terms of independent research and development of core algorithms and full lifecycle data integration, which lags behind advanced levels abroad.

2.Overview of the Entire Lifecycle of Mechanical Manufacturing

2.1 Concept and Process of the Whole Life Cycle of Mechanical Manufacturing

The full life cycle of mechanical manufacturing refers to the complete closed-loop process from product demand analysis, through design and development, process planning, production and manufacturing, assembly and debugging, sales and use, maintenance and upkeep, to final scrapping and recycling. This process presents significant stage characteristics and close internal connections: the design stage determines more than 70% of the cost and performance of the product, and its output three-dimensional model and process parameters directly guide manufacturing execution; During the manufacturing phase, design intent is achieved through material conversion and precision control, while the process data generated feeds back into design optimization; During the operation and maintenance phase, equipment status monitoring and performance feedback are used to form improvement basis for the preceding stages.

In the digital environment, deep collaboration is achieved through data flow at all stages of the entire lifecycle. For example, CAD models in the design phase can be directly imported into CAM systems to generate machining programs, and IoT devices in the manufacturing process can collect machining data in real-time, compare it with design parameters, and generate deviation analysis reports; The sensor data during the operation and maintenance phase is processed through cloud computing platforms to provide reliability improvement suggestions for the design of next-generation products. This "data-driven" process reconstruction breaks the information silos in various stages of traditional manufacturing and creates conditions for the comprehensive penetration of artificial intelligence technology.

2.2 Problems in the Entire Lifecycle of Traditional Mechanical Manufacturing

The traditional mechanical manufacturing model has many pain points in full lifecycle management. During the design phase, excessive reliance on engineer experience leads to insufficient innovation and long iteration cycles for multiple solutions. Taking automotive engine design as an example, traditional parameter optimization requires repeated physical prototype testing, and the development cycle often exceeds 18 months; Meanwhile, the disconnect between design and manufacturing processes can easily lead to "manufacturability" issues. According to industry statistics, about 30% of design changes stem from process conflicts during the manufacturing process.

The core issue faced during the manufacturing phase is the contradiction between production efficiency and quality stability. Traditional production lines use fixed process parameters, which are difficult to adapt to fluctuations in raw material performance and changes in equipment status, resulting in high scrap rates; Production scheduling relies on manual experience, and in the multi variety and small batch production mode, equipment utilization is usually less than 60%. According to statistics from a certain heavy machinery factory, downtime caused by poor process connections accounts for over 25% of the total production time.

The operation and maintenance phase is limited to passive maintenance mode, and equipment failures are mostly dealt with after the fact, resulting in huge losses from unplanned downtime. Traditional time-based preventive maintenance faces the dilemma of "excessive maintenance" or "insufficient maintenance". Data from a wind power company shows that when adopting a regular maintenance strategy, maintenance costs account for 35% of the equipment's total lifecycle costs, of which about 40% are unnecessary replacement operations. In addition, the inventory management of spare parts is extensive, often resulting in a phenomenon of "backlog and shortage coexisting", with a capital occupancy rate of up to 20% of the company's current assets.

3.Application and Optimization of Artificial Intelligence Technology in the Design Stage of Mechanical Manufacturing

3.1 Artificial Intelligence Helps Innovate Design Methods

3.1.1 Design optimization based on genetic algorithm

Genetic algorithms simulate natural selection and genetic mechanisms in biological evolution, achieving multi-objective optimization solutions through encoding, selection, crossover, mutation, and other operations, demonstrating unique advantages in optimizing mechanical structural parameters. The core principle is to transform design variables into "chromosomes", evaluate the advantages and disadvantages of schemes through fitness functions, and iteratively screen for the optimal solution. In the design of engineering robotic arms, genetic algorithms are used to optimize 12 parameters such as arm length and cross-sectional dimensions, which can reduce self weight by 15% -20% while satisfying strength and stiffness constraints. The optimization case of a certain excavator working device shows that the traditional trial and error method requires 200 iterations to converge, while the genetic algorithm only requires 50 iterations to obtain a better solution, resulting in a 75% increase in design efficiency.

3.1.2 Design Optimization Based on Neural Networks

Neural networks simulate the connectivity patterns of human brain neurons through multi-layer nonlinear mapping, possessing strong self-learning and generalization abilities, and are particularly suitable for handling multi factor coupling problems in complex mechanical systems. In material performance design, alloy composition and heat treatment parameters are used as input layers, and mechanical properties are used as output layers. A high-precision prediction model can be established through BP neural network training. The design practice of a certain high-strength steel shows that the prediction error of this method for yield strength is less than 3%, which is more than 60% lower than traditional empirical formulas. In terms of mechanism dynamics optimization, recursive neural networks can simulate the dynamic response of mechanical systems. Through neural network optimization, the positioning accuracy of a precision machine tool feed system has been improved from 0.01mm to 0.005mm, and the dynamic response speed has been increased by 40%.

3.2 Innovative Design Concepts Based on Artificial Intelligence

3.2.1 Biomimetic Design

Biomimetic design achieves mechanical system innovation by simulating biological structures and functions, and artificial intelligence technology provides efficient tools for this process. Image recognition algorithms based on deep learning can extract feature parameters from biological morphology databases and generate bio like structures through topology optimization. In the design of the robotic arm, the MIT team used convolutional neural networks to analyze the motion characteristics of octopus tentacles and developed a flexible robotic arm with 32 degrees of freedom, which has a gripping adaptability three times higher than traditional structures. A certain agricultural machinery research institute simulated the jumping mechanism of locusts' hind legs through AI, and designed a small seeder with a

50% increase in obstacle crossing ability and a 25% reduction in energy consumption.

3.2.2 Adaptive Design

Adaptive design emphasizes the real-time response capability of mechanical systems to environmental changes, and AI algorithms are the core to achieve this goal. By combining sensor data with reinforcement learning, devices can autonomously adjust parameters to maintain optimal performance. In high-precision machining equipment, an adaptive control system based on Q-learning can compensate for errors caused by temperature changes in real time. After applying this technology to a certain horizontal machining center, the dimensional accuracy stability of long-term machining has been improved by 60%. In marine engineering equipment, adaptive pile leg design utilizes AI to analyze wave load data, dynamically adjust structural stiffness, and improve platform wave resistance by 40% while reducing self weight by 15%.

3.3 Development of Intelligent Design Software and Platforms

3.3.1 Intelligent Upgrade of CAD/CAE/CAM Software

Traditional CAD/CAE/CAM software has gradually integrated AI functional modules to achieve intelligent assistance in the design process. The newly added Knowledge Based Engineering (KBE) module in the CAD system can automatically retrieve similar design cases and generate initial solutions. After being applied by a certain automotive parts enterprise, the design cycle for new parts has been shortened by 40%. The machine learning algorithm introduced in CAE analysis can establish a surrogate model based on historical simulation data, reducing the mechanical analysis time of complex structures from hours to minutes while maintaining an accuracy of over 95%. The AI process planning module of the CAM system can automatically generate optimal cutting parameters based on material characteristics and equipment status. In the machining of a certain aircraft engine blade, this technology has extended tool life by 30% and improved machining efficiency by 25%.

3.3.2 Application and advantages of cloud design platform

The cloud design platform relies on cloud computing resources to achieve multi terminal collaborative design, with AI technology responsible for intelligent retrieval, version management, and conflict detection functions. The platform understands design requirements through natural language processing technology and automatically pushes relevant standards and cases; A conflict detection algorithm based on graph neural networks can identify parameter conflicts in real-time in multi team parallel design. The global collaborative design project of a multinational construction machinery enterprise shows that after adopting a cloud based AI platform, the number of design changes is reduced by 50%, and the efficiency of cross regional team communication is improved by 60%. In addition, AI energy consumption analysis tools on cloud platforms can evaluate the carbon emissions of products throughout their entire lifecycle during the design phase, providing quantitative basis for green design.

4.Application and Optimization of Artificial Intelligence in the Mechanical Manufacturing Stage

4.1 Construction and Key Technologies of Intelligent Manufacturing Systems

4.1.1 Analysis of Intelligent Manufacturing System Architecture

The intelligent manufacturing system adopts a three-layer architecture of "perception layer network layer application layer", with AI technology playing a core role in each layer. The perception layer collects real-time data through industrial sensors, machine vision and other devices, and implements data preprocessing and anomaly detection based on edge AI chips. The visual inspection system of an electronic assembly line adopts a lightweight CNN algorithm, with a defect recognition speed of 300 frames per second and an accuracy rate of 99.7%; The network layer relies on 5G and industrial Ethernet to build low latency data transmission channels, and AI traffic scheduling algorithms can ensure the priority transmission of critical data. A certain smart factory has shortened the communication response time between devices to less than 10ms through this technology; The application layer includes functional modules such as production scheduling and quality control. The decision system based on deep learning can achieve dynamic optimization. The AI scheduling system in a certain automotive welding

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workshop has increased the balance rate of the production line from 75% to 92%.

4.1.2 Key Technology Integration and Application

The effective operation of intelligent manufacturing systems relies on the integration of AI with technologies such as big data, the Internet of Things, and digital twins. In a certain engine cylinder block machining line, more than 300 real-time parameters collected by IoT devices are cleaned by a big data platform and input into an LSTM neural network to predict machining quality deviations with an accuracy rate of 92%; The digital twin model maps the physical device status through AI algorithms, achieving virtual debugging and process optimization, and shortening the production cycle of the new production line by 40%. The elastic computing power provided by cloud computing supports large-scale training of AI models. A certain bearing enterprise, through cloud based federated learning, jointly trained a quality prediction model with multiple factories while protecting data privacy, reducing the error rate by 15%. The collaborative application of these technologies has built a closed-loop system of "physical entity digital virtual entity AI decision-making".

4.2 Optimization of Intelligent Manufacturing Execution Process

4.2.1 Process Parameters and Path Optimization

AI algorithms analyze historical processing data to construct a mapping relationship between process parameters and quality indicators, achieving dynamic optimization. In the milling process of aviation titanium alloy parts, a parameter optimization system based on reinforcement learning can adjust cutting speed, feed rate and other parameters in real time, reducing surface roughness by 30% and tool wear by 25%. In terms of path optimization, the improved A * algorithm combined with a three-dimensional model of workshop layout is used to plan the optimal path for AGV material transportation. After application in a construction machinery factory, the material delivery time is reduced by 40% and AGV energy consumption is reduced by 20%. For complex surface machining, the deep learning based tool path generation algorithm can automatically avoid interference areas. In the machining of a certain steam turbine blade, the CNC program generation time was shortened from 8 hours to 1 hour.

4.2.2 Quality control and intelligent fault diagnosis

The AI driven quality control system achieves full process monitoring through multi-source data fusion. A certain gearbox production line inputs machine vision images, sensor data, and spectral analysis results into a CNN-LSTM hybrid model to achieve early warning of gear machining defects, reducing the defect rate by 60%. In the field of equipment fault diagnosis, deep learning models based on vibration signals can identify 98% of early bearing faults, with a 30 day early warning compared to traditional spectrum analysis; The AI diagnostic system of a certain steel rolling mill has improved the accuracy of fault location to 95% and reduced maintenance time by 50% by analyzing motor current signals. In addition, the application of federated learning technology has solved the problem of data silos in multiple factory areas, and the generalization ability of the jointly trained fault diagnosis model has been significantly enhanced.

4.3 Deep Integration of Industrial Big Data and Artificial Intelligence

4.3.1 Collection and Processing of Industrial Big Data

The sources of industrial big data cover multiple dimensions such as equipment sensors, production execution systems (MES), ERP, etc. Its processing requires key steps such as data cleaning and feature engineering. AI technology plays an important role in data preprocessing: outlier detection based on clustering algorithms can remove 10% -15% of invalid data; The automatic feature extraction algorithm can extract more than 200 effective features from the original vibration signal, which is 10 times more efficient than manual screening. The big data platform of a certain steel enterprise adopts a federated learning framework to achieve collaborative analysis of data from various factories without sharing raw data, resulting in a 40% increase in data processing efficiency. The deployment of edge computing nodes enables the real-time data processing delay to be controlled within 50ms, meeting the high-precision control requirements.

4.3.2 Application of Industrial Big Data Analysis Driven by Artificial Intelligence

The deep mining of industrial big data by AI algorithms provides multidimensional support for manufacturing process optimization. In terms of energy consumption management, the AI analysis system of a cement plant identified three key optimization points by correlating production parameters with energy consumption data, resulting in an 8% reduction in unit product electricity consumption; In the field of equipment efficiency analysis, the OEE prediction model based on random forest can provide a 2-hour warning of performance decline trend. After application in a certain automotive welding workshop, the comprehensive efficiency of the equipment increased by 12%. In production scheduling optimization, an improved genetic algorithm combined with real-time order data dynamically adjusted production plans, resulting in a 30% reduction in delivery cycle and a 25% reduction in work in progress inventory for a certain household appliance enterprise. These applications indicate that the integration of industrial big data and AI is shifting from passive analysis to active decision-making.

5. Application and Optimization of Artificial Intelligence in the Operation and Maintenance Stage of Mechanical Manufacturing

5.1 Intelligent Fault Diagnosis and Predictive Maintenance

5.1.1 Principles and Methods of Intelligent Fault Diagnosis Technology

Intelligent fault diagnosis uses AI algorithms to analyze equipment operation data, achieving fault type recognition and localization. Deep learning models based on vibration signals, such as CNN and Transformer, can automatically extract fault features. The diagnostic system of a certain wind turbine adopts a dual channel CNN model, and the recognition accuracy of bearing faults reaches 99.2%, which is 15% higher than traditional wavelet analysis. The combination of voiceprint diagnosis technology with Mel spectrum and LSTM network can identify 7 typical faults in hydraulic systems. After the application of a certain injection molding machine, the early fault detection rate increased by 50%. For complex electromechanical systems, the integration of knowledge graph and deep learning has achieved root cause analysis of faults. The diagnostic system of a certain machine tool factory can locate 90% of composite faults within 30 seconds, guiding maintenance personnel to quickly troubleshoot.

5.1.2 Predictive Maintenance Strategy and Implementation

Predictive maintenance is based on AI predictive models to determine the optimal maintenance timing and achieve "on-demand maintenance". The AI prediction system of a certain subway vehicle depot predicted the wear trend 14 days in advance by analyzing wheelset vibration data, extended maintenance intervals by 50%, and avoided 3 major failures. The implementation process is divided into three stages: data collection, model training, and decision execution: deploying edge sensors to collect real-time data; Cloud trained temporal prediction models (such as Temporal Fusion Transformer) achieve Remaining Life (RUL) prediction; Finally, the maintenance plan is generated through optimization algorithms. The practice of a certain petrochemical enterprise shows that predictive maintenance reduces maintenance costs by 30%, increases equipment availability by 20%, and has a return on investment cycle of about 18 months.

5.2 Mechanical Performance Optimization and Maintenance Plan Scheduling

5.2.1 Artificial intelligence methods for optimizing mechanical performance

AI technology achieves dynamic optimization of mechanical systems by analyzing the correlation between operational data and performance parameters. In engine performance tuning, reinforcement learning algorithms can automatically optimize parameters such as fuel injection timing and throttle opening. After being applied to a certain car engine, fuel efficiency increased by 5% and emissions decreased by 8%. For wind power equipment, a deep learning model based on meteorological data and power generation efficiency can adjust blade angles in real time, increasing power generation by 10%. The AI performance optimization system of a certain shield tunneling machine extends tool life by 30% and improves construction efficiency by 25% by analyzing geological data and propulsion parameters. These methods break through the limitations of traditional empirical tuning and achieve continuous dynamic optimization of performance.

5.2.2 Intelligence of Maintenance Planning and Scheduling

AI optimization algorithms can balance

maintenance requirements and production plans, achieving efficient resource allocation. The scheduling system of a certain aircraft engine maintenance workshop adopts an improved genetic algorithm, which reduces equipment idle time by 35% while meeting skill matching and schedule constraints. In multi device collaborative maintenance, the scheduling model based on graph neural network can identify critical paths. After application in a certain chemical plant, the maintenance downtime of the entire plant was reduced by 20%. By combining virtual maintenance simulation with digital twins, process conflicts can be detected in advance, and the AI scheduling system of a certain nuclear power plant has shortened the overhaul cycle by 15 days. In addition, natural language processing technology transforms maintenance manuals into intelligent decision support, increasing the fault handling efficiency of novice maintenance personnel by 60%.

5.3 Consumables Management and Inventory Optimization

5.3.1 AI based consumables demand forecasting

The AI prediction model achieves accurate prediction of consumable demand by analyzing historical consumption data, production plans, and external factors. The LSTM demand forecasting system of a certain machine tool factory controls the prediction error of tool consumption within 8%, which is 12% lower than the traditional exponential smoothing method. The XGBoost model, which considers seasonal fluctuations, performs well in bearing inventory prediction. After being applied by a certain automotive parts enterprise, the prediction accuracy has increased by 20%. For scenarios involving multiple varieties and small batches, federated learning models can aggregate similar product data, resulting in a 15% improvement in consumable prediction accuracy for a precision instrument factory. These technologies have shifted consumables management from "passive response" to "active material preparation", significantly reducing capital occupation.

5.3.2 Inventory optimization strategy and implementation

AI driven inventory optimization achieves a balance between cost and service level by dynamically adjusting safety stock and replenishment strategies. The inventory optimization system of a certain construction machinery enterprise adopts reinforcement learning algorithm to adjust replenishment points based on real-time consumption speed, resulting in a 30% increase in inventory turnover and a 40% decrease in out of stock rate. Combining the Internet of Things with an intelligent shelving system, real-time inventory monitoring is achieved through RFID and AI counting algorithms, resulting in a 90% increase in inventory efficiency for a certain automated warehouse. For cross-border supply chains, a global inventory allocation model based on graph neural networks can balance regional demand differences. After being applied by a hydraulic parts enterprise, cross-border transfer costs were reduced by 25%. These strategies have transformed inventory management from "experience judgment" to "data-driven" precision decision-making.

6. Conclusion

This study systematically reviewed the current application status and optimization results of artificial intelligence technology in various stages of the entire life cycle of mechanical manufacturing, and constructed a complete AI application framework from design to operation and maintenance. Research has shown that AI technology significantly enhances the flexibility and economy of mechanical manufacturing systems by empowering design innovation, improving manufacturing efficiency, and optimizing operation and maintenance services. In the design phase, the application of genetic algorithms and neural networks shortens the research and development cycle by 30-50%; Intelligent optimization systems during the manufacturing phase can reduce costs by 12-18%; The predictive maintenance strategy during the operation and maintenance phase improves equipment availability by 20-30%.

The study also reveals that current applications still face multiple challenges such as data quality, technology integration, and cost control, which need to be addressed through interdisciplinary research and industry collaboration. In the future, we should focus on breakthroughs in key technologies such as small sample learning and interpretable AI, and build a standardized technical system and ecological platform. With the continuous iteration of AI technology and the deepening of industrial practice, the optimization of the entire life cycle of mechanical manufacturing will develop towards a smarter, greener, and more efficient direction, ultimately achieving a leap from "intelligent manufacturing" to "smart manufacturing" and providing core driving force for the high-quality development of the manufacturing industry.

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