Investigation on Intelligent Technologies for Construction Machinery

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Abstract. With the rapid advancement of global infrastructure development, conventional manual operations have emerged as a critical bottleneck limiting the efficiency, safety, and quality of construction site operations. Leveraging the remarkable progress in artificial intelligence (AI) technologies, intelligent construction machinery has been recognized as an innovative solution to overcome the inherent limitations of manual operations. This paper first conducts an in-depth investigation into the current application status and development trends of AI technologies in several representative global construction machinery enterprises. Secondly, through a comparative analysis between Chinese and foreign construction machinery enterprises, it identifies the shortcomings of China's construction machinery industry in AI technology application. Finally, several research prospects for AI are proposed.

Keywords: Artificial intelligence (AI), Construction Machinery, Smart manufacturing.

1 Introduction

The construction machinery industry serves as a critical pillar of the national economy [1], undertaking the construction of various heavy-duty industrial infrastructures such as transportation, water conservancy, national defense, and urban development [2]. In recent years, amid the significant restructuring of the global manufacturing landscape and the urgent demand for sustainable development, countries including China, Germany, and the United States have formulated intelligent manufacturing strategies [3-5]. Against this backdrop, networked manufacturing, wireless cloud networks, and embedded systems have demonstrated exceptional performance in artificial intelligence (AI) applications for construction machinery [6-8].

Over the past few years, several reviews have explored the literature related to AI applications in construction machinery. However, we observe that previous studies largely lack comparative analyses between Chinese and foreign construction machinery enterprises. To address this gap, this paper clarifies the research methodology, technical scope, and object selection criteria upfront, systematically investigates the practical implementation of AI by Chinese and foreign enterprises in design optimization, production automation, equipment operation and maintenance (O&M), and market

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forecasting, quantifies the development gaps, and proposes prospects for future AI development.

2 Applications of State-of-the-Art Intelligent Techniques

2.1 Research Methodology

To ensure the objectivity and reliability of findings, this study adopts a data triangulation approach, drawing data from four sources:

(1) Technical documents, including enterprise annual reports, intelligent strategy white papers (e.g., Caterpillar's 2023 AI in Construction Report, Komatsu's 2024 Smart Construction Technology Roadmap), and product technical specifications.

(2) Patents and literature, with AI-related patents retrieved from the USPTO and CNIPA using the keyword combination "construction machinery + AI + patent" (2018–2025).

(3) Primary research, encompassing in-depth interviews with R&D directors of 12 enterprises (6 global leaders, 3 Chinese head enterprises, 3 innovative SMEs) and on-site visits to XCMG's Xuzhou intelligent factory and Komatsu's Tokyo R&D center.

(4) Third-party databases, such as global market reports from Off-Highway Research, R&D investment statistics from Statista, and product performance test data from ICETA.

2.1.1 Definition of AI Technology Scope.

Consistent with the ISO/TS 15066 standard for industrial robot AI, this study defines AI as data-driven learning systems, excluding traditional rule-based automation (e.g., PLC logic control, preset threshold alarms). It specifically covers three categories:

(1) Machine learning (e.g., Random Forest for fault diagnosis, SVM for equipment state classification, GBDT for market demand prediction).

(2) Deep learning (e.g., CNN for material property prediction, LSTM for time-series data analysis, Transformer for unstructured data processing).

(3) Reinforcement Learning (RL) (e.g., TBM autonomous tunneling control, excavator path optimization).

2.1.2 Selection of Research Objects.

Following the principle of "technical leadership + innovation diversity," the research objects are selected as follows:

(1) Foreign enterprises: Market leaders (Caterpillar, Komatsu, Volvo Construction Equipment) accounting for 42% of global construction machinery AI patent applications (2018–2025) and 33% of global market share; innovative SMEs (Built Robotics, Dusty Robotics) focusing on niche cutting-edge technologies.

(2) Chinese enterprises: 5 head enterprises from the 2025 Global Top 50 Construction Machinery Manufacturers (XCMG, SANY Heavy Industry, Zoomlion, Liugong, CRCC Heavy Industry), representing 78% of China's construction machinery AI

market scale, with distinct AI application strategies (e.g., XCMG's excavator autonomous driving, SANY's crane remote O&M).

2.2 Core Applications of Intelligent Techniques

2.2.1 Design Optimization and Simulation.

Artificial intelligence (AI) has revolutionized product design paradigms by enabling data-driven parameter optimization and enhancing simulation fidelity. Unlike conventional experience-dependent methodologies, AI algorithms leverage large-scale dataset analytics to generate globally optimal solutions. For instance, Volvo Group achieved a 15% improvement in excavator fuel efficiency through the implementation of digital twin technology, while simultaneously enabling real-time operational simulation for virtual validation of design schematics, thereby significantly reducing R&D expenditures. Caterpillar Inc. utilized Convolutional Neural Networks (CNNs) for material property prediction, resulting in a 20% reduction in new material development cycles. Notably, Reinforcement Learning (RL)-based optimization algorithms outperform traditional approaches such as Genetic Algorithms (GAs), which are prone to local optima convergence; RL frameworks dynamically adapt to complex environments, ensuring the attainment of globally optimal solutions. Komatsu Group further exemplifies this by integrating localized environmental constraints into AI-driven design processes, optimizing excavator performance for the high-temperature and high-humidity conditions of Southeast Asia, which has contributed to substantial regional market share growth.

2.2.2 Production Automation and Intelligent Manufacturing.

AI integrates robotics and automation systems to realize production line intelligence. AI-driven industrial robots adjust operational parameters based on sensor feedback to ensure quality consistency in welding and assembly. Predictive maintenance, powered by SVM (for small-sample early fault detection) and LSTM (for time-series data-driven operational prediction), minimizes downtime. Komatsu's AI-enabled smart factories increased production efficiency by over 30% and reduced maintenance costs by 15%. Built Robotics emphasizes green manufacturing, using AI to optimize hydraulic system design and production, cutting energy consumption and carbon emissions.

2.2.3 Intelligent Operation and Remote Monitoring.

AI transforms O&M from periodic inspections/post-failure repairs to precision maintenance. IoT sensors collect real-time operational data, which is analyzed via big data and machine learning for fault prediction. SANY's "SYMC" system reduces equipment failure rates by 40% and maintenance costs by 25% through real-time monitoring of key parameters. Remote monitoring enhances management flexibility for remote projects: John Deere's platform enables global real-time tracking of equipment location and status using Random Forest and GNN; Caterpillar's "Cat Connect" offers full-lifecycle management with standardized global services.

2.2.4 Market Forecasting and Customer Behavior Analysis.

AI enables sophisticated market demand forecasting by synthesizing multi-source data streams, including historical sales figures, macroeconomic indicators, and unstructured social media sentiment. XCMG Group exemplifies this through the integration of Gradient Boosting Decision Trees (GBDTs) for structured data analysis (e.g., economic indices) and Transformer architectures for unstructured data processing (e.g., policy documents, social media trends), which collectively enabled the accurate identification of growth potential in Southeast Asia, driving a 35% year-on-year sales increase in the region. Hitachi Construction Machinery leveraged AI to model the impact of climate change on infrastructure development patterns, predicting accelerated growth in African markets and launching specialized equipment adapted to high-temperature and arid environmental conditions, thereby gaining a competitive market advantage.

3 Comparison of Leading Enterprises and Research Prospects

Table 1. Top 9 global construction machinery manufacturer.

Company	Country	2025 Market share (%)
Caterpillar	USA	13
Komatsu	Japan	10.4
Volvo	Sweden	9.6
XCMG	China	7.9
SANY	China	7.5
Zoomlion	China	4.9
John Deere	USA	4.7
Hitachi	Japan	4.5
Liebherr	Germany	4.1

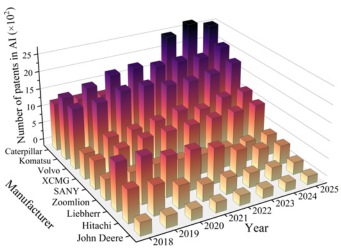

Fig. 1. Top 9 global construction machinery manufacturer.

As illustrated in Fig. 1 and Table 1, during the "14th Five-Year Plan" period, under the leadership of the Communist Party of China, China's construction machinery industry has achieved leapfrog development. However, compared with leading foreign enterprises, the number of patents in the AI domain within China's construction machinery industry remains relatively low, necessitating continued efforts from enterprises in this sector.

3.1 Quantitative Analysis of Development Gaps

A three-level indicator system quantifies the AI gap between Chinese and foreign enterprises:

3.1.1 R&D Investment.

During 2018–2025, foreign leading enterprises (Caterpillar, Komatsu, Volvo CE) allocated an average of 8.7% of total R&D investment to AI, compared to 5.2% for Chinese head enterprises (XCMG, SANY, Zoomlion). Caterpillar's annual AI R&D investment reached $1.2 billion, while XCMG's $480 million was the highest among Chinese enterprises.

3.1.2 Technical Output.

From 2018 to 2025, Caterpillar and Komatsu held 1,243 and 987 authorized AI patents, respectively, versus 428 for SANY and 396 for XCMG. Foreign patents had an average citation frequency of 18.3, significantly higher than China's 7.6, indicating stronger technical influence.

3.1.3 Product Performance.

At ICETA's test center, Komatsu PC200-11 (280 m^3/h) and Caterpillar 320 GC (272 m^3/h) outperformed XCMG XE215DA (235 m^3/h) and SANY SY215C (228 m^3/h) in autonomous excavator earthwork volume. Caterpillar's "Cat Connect" (92%) also exceeded SANY's "SYMC" (83%) in fault prediction accuracy (based on 10,000 equipment operation samples).

3.1.4 Subjective Evaluation.

Using the Delphi method, 15 industry experts scored "AI technology maturity" and "service standardization" (1=immature, 5=fully mature). Foreign leading enterprises averaged 4.2, compared to 3.1 for Chinese enterprises, reflecting gaps in comprehensive technical application.

3.2 Research Prospects

Despite certain achievements in the application of AI technology in the construction machinery industry, substantial room for innovation persists. The following are several noteworthy directions.

(1) Multimodal data fusion integrates visual, acoustic, and vibration data to enhance model accuracy—Bosch improved fault diagnosis by 20% via audio-vibration fusion, implementable with MTL in PyTorch/TensorFlow.

(2) Adaptive learning systems based on Meta-Learning and Transfer Learning reduce labeled data reliance. Hitachi's new excavators use such systems to refine control strategies via real-world data.

(3) Sustainable and green AI leverages PSO and DRL for energy optimization—Liebherr raised fuel efficiency by 10% and cut carbon emissions by 12%. AI-based recycling systems promote circular economy development..

4 Conclusion

This paper presents a systematic review of the current research status of intelligent technologies for construction machinery. From design optimization and production automation to equipment operation and maintenance, and further to market forecasting, the application scope of artificial intelligence (AI) has been continuously expanding. During the "14th Five-Year Plan" period, China's construction machinery industry has achieved leapfrog development, and intelligentization has emerged as an inevitable trend in industrial upgrading. Nevertheless, compared with the international advanced level, China's construction machinery industry still has shortcomings in AI application, and it is urgent for the industry to actively explore solutions. Looking forward, as technologies continue to mature and innovate, AI is expected to become the core driving force for promoting the transformation and upgrading of the construction machinery industry.

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