Artificial Intelligence-Driven Transformation in Civil Engineering: Key Technologies and Advances in Practice

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Abstract. Against the backdrop of rapid urbanization and growing infrastructure demands, traditional civil engineering faces dual challenges in efficiency and quality. This paper examines the innovative applications of artificial intelligence (AI) across the entire lifecycle of civil engineering, systematically exploring its technological pathways and practical outcomes in design, construction, and operation and maintenance (O&M). In the design phase, machine learning enables automated structural design and multi-objective optimization, overcoming the limitations of conventional experience-dependent approaches and significantly improving solution-generation efficiency. During construction, natural language processing (NLP) techniques optimize process organization and risk management strategies, facilitating the transition toward intelligent and precision-driven on-site operations. For O&M, the integration of deep learning and image recognition revolutionizes infrastructure crack detection, damage identification, and monitoring capabilities, providing data-driven support for informed decision-making. Through an interdisciplinary approach, this study consolidates representative case studies to elucidate the shift toward data-integrated models in AI-driven civil engineering, emphasizing the pivotal role of technological convergence in advancing industry-wide intelligent transformation. The research not only presents a practical technical framework for engineering applications but also identifies key challenges to address in future studies, aiming to accelerate the industry's transition toward efficient, safe, and sustainable intelligent construction.

Keywords: Artificial intelligence(AI), Civil engineering, Intelligent Transformation, Technological convergence

1 Introduction

The civil engineering sector is confronting unprecedented challenges in the context of rapid global urbanization and infrastructure expansion, including inconsistent construction quality control and persistent labor shortages. Conventional methodologies are proving increasingly inadequate to address these emerging demands, rendering the improvement of overall infrastructure performance a pressing concern. Notably, artificial

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intelligence (AI) has transitioned from a basic supportive tool to a sophisticated decision-making and predictive technology. This evolution presents significant opportunities to revolutionize key civil engineering processes - from design and construction to monitoring and maintenance - thereby enhancing operational efficiency, ensuring safety, and accelerating the industry's intelligent transformation [1].

This study provides a comprehensive framework for technological advancement in civil engineering, with detailed analysis of critical AI applications across all project phases to serve as a practical reference for industry professionals. The research makes dual contributions: academically, it establishes an interdisciplinary paradigm by investigating integration pathways between AI and civil engineering, thereby expanding theoretical frontiers and identifying key research priorities; practically, it synthesizes innovative technological solutions to facilitate intelligent construction practices, ultimately supporting the industry's digital transformation and sustainable development objectives.

2 Advances in Intelligent Design Methodologies

2.1 Machine Learning-based Automated Structural Design Approaches

The evolution of machine learning algorithms has enabled contemporary architectural design systems to automatically generate optimized structural solutions by processing multiple parameters, including functional requirements and material properties [2]. This technological progression signifies a paradigm shift from expert knowledge-dependent systems to adaptive intelligent systems capable of autonomous learning and optimization [3]. Recent research has introduced a generative structural design framework based on "data-mechanics-knowledge" co-learning principles, incorporating various neural network technologies such as Graph Neural Networks (GNNs) to achieve intelligent and automated structural design[4][5]. Furthermore, scholars have developed digital extraction methodologies utilizing Building Information Modeling (BIM) and Computer-Aided Design (CAD) platforms. These advancements have been complemented by the implementation of large language models and generative AI systems for structural design optimization, significantly enhancing both the efficiency and accuracy of semantic processing in design workflows [6].

2.2 Deep Learning-Based Load Impact Assessment and Design Optimization

The application of Deep Learning (DL) in structural design has gained increasing prominence, particularly in predicting and evaluating the dynamic effects of external loads or disturbances on building structures. This approach significantly enhances both the safety and adaptability of design solutions [4].

Feng Decheng et al. employed Machine Learning (ML) to predict fundamental performance indicators of concrete structures. By incorporating SHAP (Shapley Additive Explanations) methodology, they improved model interpretability, thereby addressing the inherent "black box" limitation of conventional ML approaches. Case studies demonstrate that this method surpasses traditional models in both accuracy and computational efficiency [7]. Fan Zunjun developed a framework based on OpenSees, utilizing ML techniques with NGBoost and NSGA-II algorithms for multi-objective preliminary design optimization. This approach enables effective prediction of seismic performance for RC frame structures under strong earthquakes [8]. Li Ning et al. proposed an adaptive ensemble learning surrogate model that integrates Kriging and PC-Kriging models for structural reliability analysis. Their method constructs surrogate models using limited design points, effectively replacing complex and computationally intensive original models [9].

2.3 Intelligent Generation Technology for Construction Drawing Schemes

Artificial intelligence technologies are fundamentally transforming conventional construction drawing production processes, delivering substantial improvements in both efficiency and accuracy. As illustrated in Figure 1, the TransBIM platform employs advanced algorithms to automatically extract information from CAD schematic drawings and generate corresponding BIM models. Following comprehensive collision detection, model verification, structural analysis, and MEP system evaluation, the platform efficiently produces complete sets of construction drawings. Shanghai Construction Group has developed an intelligent construction scheme generation cloud platform that utilizes multi-source semantic correlation algorithms. This system enables rapid generation of equipment deployment plans and technical disclosure documents. Furthermore, through the implementation of drawing object generation algorithms, the platform's intelligent CAD drafting plugin can automatically produce standardized construction drawings [10].

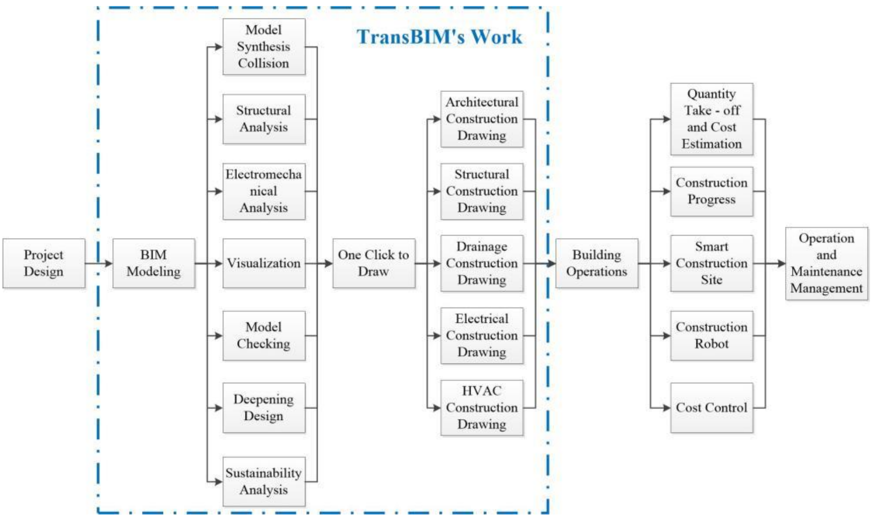

Fig. 1. Workflow of the TransBIM Platform

3 Intelligent Construction Technologies and Automation

3.1 Construction Drawing Information Extraction

Construction drawings serve as fundamental documentation in building construction. Current natural language processing (NLP) technologies have demonstrated capabilities in mining tacit knowledge from routine civil engineering documents, including processing unstructured engineering documentation, extracting structural slab information, and generating explanatory texts [11][12]. To enhance information extraction accuracy, several methodological improvements can be implemented: optimization of morpheme databases, advancement of syntactic analysis techniques, and integration of semantic comprehension. For efficiency enhancement, high-performance models such as BERT (Bidirectional Encoder Representations from Transformers) prove particularly effective. These models leverage parallel computation mechanisms and employ fine-tuning of pre-trained models to automate and optimize the extraction workflow [13].

3.2 Optimization of Construction Organization Plans

Natural Language Processing (NLP) offers multifaceted approaches to enhance construction organization planning. A notable application involves extracting key themes and sentiment analysis from public discourse regarding transportation, environmental concerns, and public service expectations. This data-driven approach provides valuable references for smart urban planning optimization [14]. Furthermore, the integration of expert-level robotic systems in construction projects demonstrates significant potential. These advanced systems address critical challenges in technical report generation, particularly in the precise identification and extraction of key elements for assessment reports. Such capabilities substantially improve the efficiency and accuracy of feasibility report compilation processes.

3.3 Risk Information Management

Natural Language Processing (NLP)-based text classification enables automated risk assessment through construction report analysis. Word embedding techniques such as Word2Vec facilitate semantic understanding of critical concepts, thereby enhancing risk evaluation accuracy. As illustrated in Figure 2, the integration of Long Short-Term Memory (LSTM) networks with Principal Component Analysis (PCA) allows for comprehensive analysis of on-site reports to identify emerging risk patterns. Transformer architectures demonstrate superior performance in extracting key risk factors and corresponding mitigation measures, while sentiment analysis, named entity recognition, and machine translation each contribute distinct capabilities to the risk management framework[15][16]. In practical applications, NLP technologies have been successfully implemented for drawing analysis, risk monitoring through construction logs, and even engineering ethics education[17][18]. Contemporary intelligent risk management systems have achieved remarkable results in actual projects. Figure 3 demonstrates the AI-powered monitoring platform deployed at the Xudapu Nuclear Power Project, which features real-time detection of safety violations and triggers multi-level warning mechanisms. Similarly, the Zhongnan Electric Power Tianmen Jiangchang Wind Farm project has established a comprehensive "1+2+N" hierarchical management system for renewable energy projects. This system integrates cloud computing, big data analytics, IoT, mobile technology, and AI to create a multi-source data fusion platform for risk prevention and control [19].

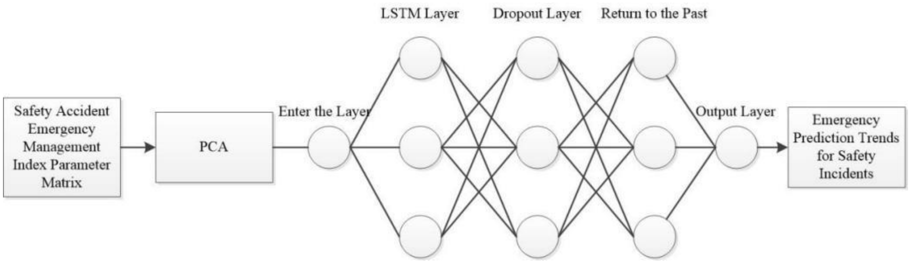

Fig. 2. LSTM Network Topology for Predicting Rolling Bearing Degradation Trends [22]

(a) (b)

Fig. 3. Application of AI-Based Intelligent Analysis Technology in Nuclear Power Construction at the Xudapu Nuclear Power Project(a. Smart Construction Management Platform of the Xudapu Nuclear Power Project;b.Construction Site of the Reactor Building for Unit 3)

4 Intelligent Infrastructure Operation and Maintenance

4.1 Crack Detection and Structural Damage Identification

The emergence of deep learning has precipitated a paradigm shift in crack detection methodologies, transitioning from conventional image processing techniques to DL-based approaches [20]. Hsieh et al. categorized deep learning-based crack detection algorithms into three distinct groups according to their functional purposes: image classification algorithms, object detection algorithms, and image segmentation algorithms, all of which have demonstrated successful applications in crack detection [21]. Yu Haiyang's research team enhanced the U-Net architecture by developing a novel road crack detection model incorporating both residual connections and attention mechanisms [21]. Cha et al. capitalized on the autonomous feature extraction capability of deep convolutional neural networks to establish a vision-based concrete crack detection system. Their customized CNN achieved an impressive 98% recognition accuracy and, when integrated with sliding window technology, enabled comprehensive scanning of images exceeding 256×256 pixels [11].

In structural damage assessment, deep learning techniques have shown particular efficacy in heritage conservation. The implementation of Faster R-CNN models with ResNet101 frameworks has enabled automated detection of weathering and spalling damage in historical brick masonry structures [22]. Similarly, the combination of deep learning with power spectral density analysis has proven effective for damage identification in steel frame structures, collectively underscoring machine learning's transformative potential in structural health monitoring [23]. Addressing data integrity challenges in damage assessment, Xie Xiaokai et al. developed a correlation model using BP neural networks that successfully reconstructs missing data segments, providing an effective solution for long-term stress monitoring in large-span spatial structures [4]. Parallel research by Na et al. employed genetic algorithms for shear structure damage identification, achieving significant improvements in assessment efficiency [4]. Karve et al. advanced the field further through their digital twin framework, which integrates damage diagnosis, prognosis, and mission optimization. Their Gaussian Process model, trained within the digital twin environment, attained a remarkable 1.19% error rate, demonstrating reliable performance optimization while maintaining stringent safety standards [24].

4.2 Other Applications of AI Technology in Infrastructure Operation and Maintenance Management

At the level of intelligent hardware, the intelligent inspection robot is equipped with multi-spectral camera, infrared thermal camera and environmental sensors, which supports autonomous navigation and equipment abnormality identification, realizes automatic inspection of equipment status in the machine room, shortens the fault response time, reduces the workload of manual inspection, and combines with the digital twin technology to synchronously generate the equipment health assessment report [25]. At the data system level, in the whole life cycle of operation and maintenance of Shanghai Railway Line 18 project, the application of “BIM+IoT” technology realizes the seamless transmission of BIM data in the whole period, and the operation and maintenance stage is based on the completed digital assets, lightweight shared model data, automatic integration of IoT and OT data, driving the standardization of operation and maintenance management, and helping the Station operation and maintenance digital transformation [26]. The HUALUXE Nanjing Yangtze River project is committed to creating an exquisite macro BIM management platform and integrating various types of intelligent system data, linked room data, monitoring data, etc., to realize the digital twinning of the hotel's building assets.

5 Conclusions

This paper systematically examines critical technologies and practical advancements in artificial intelligence (AI)-enabled intelligent transformation of civil engineering, with particular focus on three core domains: design, construction, and operation/maintenance. The study elucidates the pivotal role of technological integration in enhancing engineering efficiency, optimizing resource management, and driving industry innovation. Through comprehensive analysis of domestic and international research cases and technological pathways, the article establishes both theoretical foundations and practical references for industry-wide intelligent upgrading, while highlighting the transformative potential of interdisciplinary collaboration in transcending traditional engineering boundaries.

The research reveals consistent patterns in AI applications across civil engineering processes: structural design automation and multi-objective optimization through machine learning in the design phase; construction process management efficiency gains via natural language processing (NLP); and enhanced monitoring/repair capabilities through deep learning and image recognition technologies during operation/maintenance. Despite significant variations in technical approaches, these applications share a fundamental data-driven paradigm, where algorithmic innovation and multi-technology integration collectively facilitate the industry's transition from experience-based to intelligent decision-making frameworks [27][28].

Three critical challenges emerge in current AI applications for civil engineering: The "black box" nature of machine learning (ML) algorithms compromises decision reliability in design, necessitating physics-informed model development; The absence of interactive frameworks for multi-source heterogeneous data in construction demands lifecycle data coordination systems; Inefficient multi-modal data fusion in maintenance requires cross-modal correlation models incorporating damage mechanisms. Future research directions should prioritize:(1) Physics-guided intelligent algorithms for reliable decision-making; (2) Data standardization and dynamic integration to overcome collaboration barriers; (3) Cross-modal fusion and mechanism-enhanced technologies for improved damage prediction. Only through deep integration of algorithms, data, and physical principles can the civil engineering industry achieve comprehensive intelligent transformation across the entire project lifecycle, ultimately realizing the new paradigm of intelligent construction.

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