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ARTIFICIAL INTELLIGENCE EMPOWERING NUCLEAR POWER EPC FULL-PROCESS COLLABORATIVE MANAGEMENT

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Abstract: As a typical ultra-large-scale, strongly coupled, and high-safety-level complex system engineering, nuclear power engineering involves multi-stage, multi-professional, and multi-stakeholder collaborative links throughout its full life cycle, including design, procurement, construction, commissioning, and operation and maintenance. Traditional management models generally face problems such as prominent information silos, inconsistent professional interfaces, high supply chain risks, lagging construction monitoring, and heavy pressure on quality and safety management, which are difficult to meet the requirements of current large-scale nuclear power construction and digital transformation. With the rapid development of artificial intelligence, big data, digital twin, BIM, and Internet of Things technologies, EPC full-process collaborative management driven by intelligent algorithms has gradually become an important development direction of nuclear power engineering management technology. This paper systematically analyzes the complexity characteristics of nuclear power engineering EPC, and constructs a full-process collaborative theoretical system of "data connection - scenario modeling - algorithm driving - platform support" from the dual perspectives of design institutes and owners. Focusing on intelligent design optimization, multi-professional collaboration, intelligent procurement management, construction progress identification and prediction, intelligent quality and safety monitoring, and operation and maintenance based on digital twins, a set of engineering implementable intelligent management schemes is proposed. Meanwhile, by constructing a cloud-edge-end integrated collaborative platform and MLOps model system, a technical architecture supporting full-life-cycle intelligent decision-making is formed. The verification results in typical nuclear power engineering projects show that artificial intelligence technology can increase design efficiency by more than 80%, reduce professional conflicts by more than 70%, lower procurement risks by 30%, decrease construction rework rate by more than 60%, and improve equipment availability to more than 98%, effectively supporting the quality improvement, cost reduction, and efficiency enhancement of nuclear power projects. The research results provide a systematic method and practical sample for the intelligent upgrading of nuclear power EPC, and have important theoretical significance and engineering value for promoting the digitalization and intelligent development of China's nuclear power industry.
Keywords: Artificial intelligence; Nuclear power engineering; EPC management; Digital twin; Intelligent design; Intelligent operation and maintenance

1 INTRODUCTION

1.1 Research Background

As an important strategic energy source with high safety, low carbon emissions, and high capacity factor, nuclear energy plays an irreplaceable role in the current energy structure transformation and the implementation of the "dual carbon goals". China's nuclear power industry has entered a critical stage of large-scale and systematic development. The number of new nuclear power projects continues to grow, design standards are constantly improved, and the complexity of the engineering system has also increased significantly. Under the national policy background of promoting "intelligent construction" and "smart nuclear power", the construction mode, management methods, and technical system of nuclear power engineering are undergoing profound changes.
Nuclear power EPC (Engineering–Procurement–Construction) projects run through multiple stages and span multiple professions, making them typical ultra-large-scale complex systems in the field of engineering construction. On the one hand, the design of nuclear power plants involves more than 30 professions, such as nuclear island, conventional island, auxiliary systems, plant structure, electrical control, and equipment layout, showing characteristics of interdisciplinary coupling, multi-physics field correlation, and large design documents. The project needs to process more than 100,000 design drawings, tens of thousands of equipment lists, and thousands of interface relationships, with complex information structures and continuous iterations. On the other hand, the safety level of nuclear power projects is much higher than that of general industrial engineering, and they must comply with multiple sets of strict international and national regulations, such as ASME, RCC-M, and HAF series standards, which put forward extremely high requirements for design consistency, quality traceability, and construction process compliance.
Under the traditional EPC management model, nuclear power engineering generally faces the following problems:
(1) Severe information dispersion. Professional models within design institutes are difficult to unify, and information is difficult to flow efficiently among owners, engineering general contractors, and equipment suppliers;

(2) Low efficiency of professional collaboration. Nuclear power design is highly dependent on manual experience, interface coordination among various professions takes a long time, design changes are frequent, resulting in a high probability of rework during the construction stage;
(3) Prominent supply chain risks. Complex equipment models, long delivery cycles, and multi-level and multi-source supply chain structures lead to opaque procurement processes and difficulty in real-time risk identification;
(4) Lagging construction monitoring. On-site progress relies on manual inspection, which has problems such as long cycles, slow feedback, and difficulty in quantifying deviations;
(5) Heavy pressure on quality and safety. Nuclear power has extremely strict requirements for welds, concrete, equipment quality, etc. Traditional manual inspection methods have the risk of missed inspections, and potential safety hazards are not identified in a timely manner;
(6) High cost during the operation and maintenance stage. There is a large number of key equipment, and health status monitoring, fault prediction, and preventive maintenance rely on a lot of manual experience, making it impossible to achieve refined management.
With the continuous expansion of information scale and the increasing complexity of engineering, the traditional manual-driven EPC management method has been difficult to meet the requirements of efficiency, safety, quality, and controllability of nuclear power engineering in the new era. There is an urgent need to build a collaborative management system centered on data fusion and intelligent algorithms.

1.2 Current Status of Domestic and Foreign Technology Development

In recent years, intelligent engineering technology centered on artificial intelligence has been rapidly applied in the international nuclear power industry. The United States' construction optimization system has combined reinforcement learning with construction schedule control to realize automatic construction path planning [1]; Europe has accumulated a lot of deep learning algorithm practices in intelligent equipment inspection and structural health monitoring [2]; Japan has adopted an expert hybrid model in nuclear fusion control and safety monitoring, which has higher real-time performance compared with traditional physical models [3].
In contrast, China's nuclear power intelligent construction started late but developed rapidly. Breakthrough achievements have been made in multiple subdivided scenarios such as intelligent design review, 3D model inspection, equipment identification, unmanned inspection, construction visual monitoring, and intelligent operation and maintenance [4-5]. Some intelligent systems have been pilot-tested in engineering in multiple nuclear power projects [6].
Overall, international research shows a trend of "systematization, platformization, and automation", while domestic research is still mainly focused on breakthroughs in several key functional points. How to achieve full-process collaboration, in-depth data sharing, and multi-model fusion is the core scientific and engineering problem facing the industry.

1.3 Research Purpose and Main Content

To solve the high-complexity collaboration problems existing in traditional nuclear power EPC projects, this paper aims to build a full-life-cycle artificial intelligence-enabled EPC collaborative management system. Taking the business logic of design institutes and owners as the main line, it constructs an integrated intelligent architecture around "design optimization - procurement control - construction monitoring - operation and maintenance prediction".
The main research contents include:
(1) Analyze the complexity characteristics and collaboration bottlenecks of nuclear power EPC projects;
(2) Propose intelligent parametric design, multi-professional collaborative optimization, and design quality review methods;
(3) Build an intelligent supply chain risk identification, procurement demand prediction, and contract management system;
(4) Construct construction progress identification, prediction, and scheduling methods based on computer vision and time-series models;
(5) Propose a quality defect identification, safety risk prediction, and intelligent training system;
(6) Build equipment health monitoring and predictive maintenance models based on digital twins and deep learning;
(7) Propose a cloud-edge-end collaborative nuclear power EPC full-process intelligent platform architecture;
(8) Verify the engineering effect of the proposed system through typical engineering cases.

1.4 Technical Route

This paper adopts the research route of "theoretical research - technology development - engineering verification", which is gradually carried out from demand proposal, algorithm modeling, system development to case evaluation, and the specific process is shown in Figure 1.

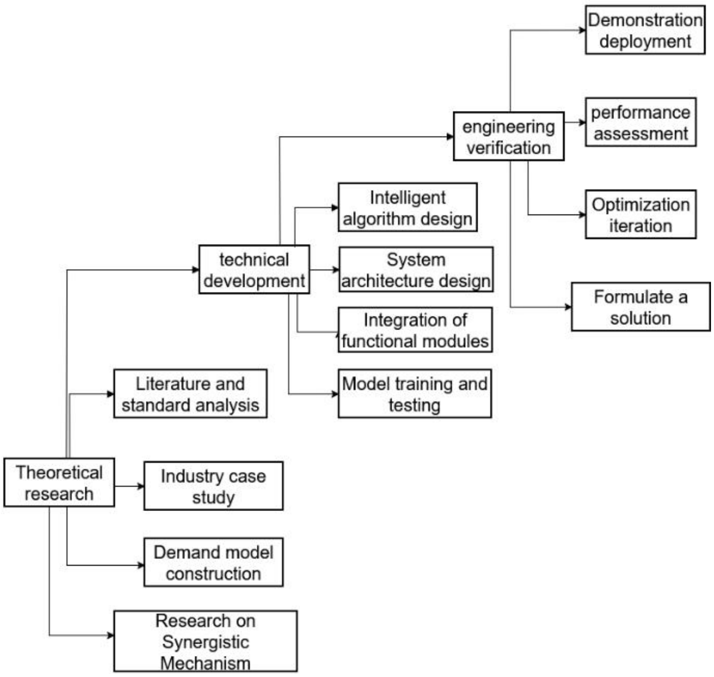

Figure 1 Technical Route

2 ARTIFICIAL INTELLIGENCE EMPOWERMENT MECHANISM FROM THE PERSPECTIVE OF DESIGN INSTITUTES

2.1 Complexity and Intelligent Requirements of Nuclear Power Design

Nuclear power engineering design is the starting point of the entire EPC full process, and its results determine the quality and cost of the procurement, construction, and even operation and maintenance stages. Due to the characteristics of cross-professional, multi-constraint, and multi-interface of nuclear power projects, the traditional design mode relying on manual experience has been difficult to meet the increasingly complex engineering requirements and support the large-scale advancement of new nuclear power projects. Therefore, introducing artificial intelligence to realize automatic design, intelligent review, and multi-professional collaboration has become an inevitable trend in the development of the industry.

2.1.1 High design complexity caused by multi-professional coupling

Nuclear power design involves more than 30 professions, such as reactor engineering, thermal hydraulics, system layout, electrical engineering, instrumentation and control, structural civil engineering, and HVAC. Each profession has independent design parameters and specification requirements, and there are a large number of coupling relationships between them. For example:

- Thermal hydraulic parameters affect equipment layout and pipeline paths;
- Structural design constraints equipment spacing, safety channels, and seismic performance;
- Instrumentation and control system parameters affect cable layout, electrical load, and construction interfaces.

This multi-professional strong coupling leads to the nonlinear characteristics of variables in the design process, making manual optimization extremely difficult.

2.1.2 Complex and multi-source parallel nuclear power design specifications

Nuclear power engineering must meet domestic regulations, international standards, and supplier technical conditions at the same time. Specification documents often include a large number of texts, diagrams, and data tables. Under manual review conditions, designers need to spend a lot of time reading and comparing, which is prone to omissions or misjudgments.

2.1.3 Large document scale and frequent version iterations

The scale of design documents for a 1 million kilowatt-class nuclear power plant usually includes:

- More than 100,000 drawings;
- More than 50,000 equipment and material lists;
- Tens of thousands of professional interface requirements;
- More than 2,000 design changes per month.

Therefore, intelligent design data management and version control tools are important guarantees for improving quality.

2.2 Intelligent Parametric Design and Optimization

Intelligent parametric design enables the system to automatically generate schemes that meet engineering standards by modeling the mapping between input parameters, constraints, and design results. Artificial intelligence can perform automatic calculation, automatic inspection, and optimization in this process.

2.2.1 Parametric design function model

The relationship between design variables and output results can be abstracted as a mapping function:

$y = f(x; \theta)$

Where:

- x represents input parameters (such as pressure, flow rate, equipment spacing);
- y represents output results (such as 2D drawings, 3D models, BOM lists);
- θ is the model parameter.

To measure the rationality of the design, a loss function can be defined:

$L = \alpha L\_perf + \beta L\_safe + \gamma L\_cost$

Where:

- L_perf represents performance deviation;
- L_safe represents safety constraint deviation;
- L_cost represents cost deviation;
- α, β, γ are weighting coefficients.

This model can be used in various scenarios such as system process schemes, equipment layout, and pipeline layout.

2.2.2 AI-driven 2D/3D model generation

Generative models based on multi-modal deep learning can accept inputs such as natural language descriptions, sketches, and existing models, and automatically generate design drawings and models. Its workflow is shown in Figure 2.

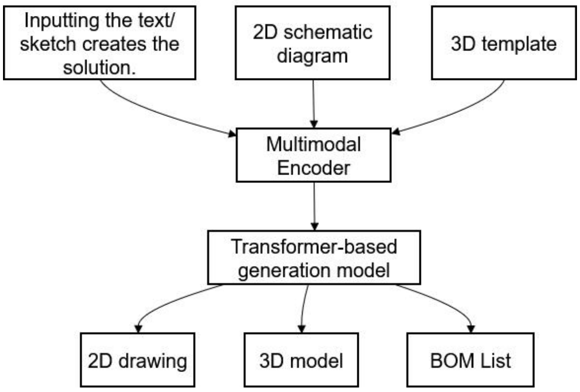

Figure 2 AI-Driven 2D/3D Model Generation Workflow

With this technology, the efficiency of the preliminary design stage can be greatly improved, freeing designers from repetitive work.

2.2.3 Multi-objective optimization methods

Nuclear power design usually needs to optimize multiple objectives simultaneously, such as:

- Minimum space occupation;
- Shortest pipeline length;
- Lowest cost;
- Optimal maintenance route, etc.

Multi-objective optimization can be defined as:

$\min F(X) = \{ f1(X), f2(X), ..., fn(X) \}$

Constraint conditions:

$gi(X) <= 0$

$hj(X) = 0$

A set of Pareto optimal solutions can be obtained through algorithms such as NSGA-II and NSGA-III for engineers to select schemes.

2.3 Intelligent Review of Nuclear Power Design Specifications

Design specification review is an important link in quality control. Artificial intelligence can improve efficiency from three aspects: knowledge extraction, constraint identification, and automatic comparison.

2.3.1 Specification knowledge extraction and structured expression

Using natural language processing technologies (such as BERT + CRF), the following can be automatically extracted from specifications:

- Quantitative constraints (such as minimum spacing $\geq$ a certain value);
- Conditional logic (such as if A is satisfied, then B must be satisfied);
- Professional terms (such as material grades, equipment codes).

The extracted knowledge can be expressed as triples:
(entity1, relation, entity2)
For example:
(Pipeline Support, Requires, Minimum Wall Thickness ≥ 6mm)
2.3.2 Specification automatic comparison algorithm
The deviation between the design result s_i and the specification requirement r_i can be defined as:
$d_i = s_i - r_i$
When $|d_i|$ > threshold, the system automatically generates review comments.
2.3.3 Multi-professional consistency check
Logical consistency verification of design documents is performed based on graph databases, such as:
- Whether equipment interfaces are consistent with pipeline connection points;
- Whether the number of cables matches the instrumentation and control system;
- Whether the layout inside the containment meets the maintenance space requirements.

AI can automatically identify potential inconsistency problems through rule reasoning.

2.4 Multi-Professional Collaboration and Collision Detection Optimization

Multi-professional collaboration is one of the core difficulties in nuclear power design. Artificial intelligence improves collaboration efficiency from three dimensions: knowledge association, model analysis, and spatial optimization.
2.4.1 Construction of nuclear power knowledge graph
The knowledge graph connects nuclear power equipment, pipelines, materials, interfaces, calculation parameters, and specification clauses into a unified semantic network to support search, review, and reasoning.
Typical triple examples:
- (Equipment A, Located in, Plant Area B)
- (Pipeline C, Connected to, Equipment D)
- (Parameter E, Restricted by, Specification Clause F)

The knowledge graph is an important foundation for realizing intelligent review and collaborative optimization.
2.4.2 Semantically enhanced collision detection
Deep learning models (such as PointNet++) can be used to extract geometric features of 3D point cloud models, enabling automatic identification of objects such as equipment, pipelines, and supports and collision detection, and the specific workflow is shown in Figure 3.

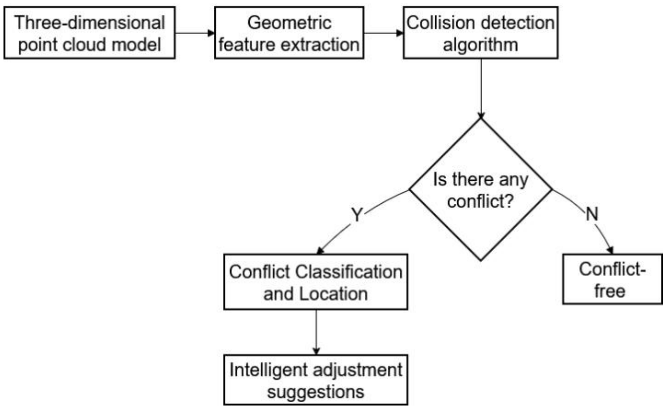

Figure 3 Semantic-Enhanced Collision Detection Workflow

Combined with semantic information, the system can distinguish negligible minor conflicts from major safety-affecting conflicts and provide intelligent adjustment suggestions.

2.5 Design Data Management and Version Control

Nuclear power design documents are extremely large in quantity and update frequency. Artificial intelligence combined with modern information technology can provide efficient data management solutions.
2.5.1 Traceable mechanism of version chain structure
The version of design documents can be managed using a chain structure:
$v_t = \mathrm{Hash}(v_{(t-1)} \| \Delta_t)$
Where:
- v_t represents the version identifier at time t;
- Δ_t represents the change content.

This structure ensures that versions cannot be tampered with and changes can be traced.
2.5.2 Hybrid retrieval system

Combining BM25 (keyword retrieval) with vector retrieval (semantic retrieval) can significantly improve the efficiency of design document search. Vector retrieval can identify semantically similar content, while BM25 can quickly lock documents containing keywords. The combination of the two can improve retrieval accuracy and recall rate.

2.6 Intelligent Guarantee System for Design Quality

Artificial intelligence can provide efficient quality control tools for complex design scenarios.

2.6.1 Neural network simulation acceleration based on physical constraints

PINN (Physics-Informed Neural Networks) can directly incorporate physical equations into the loss function to accelerate simulation solution:

$L = L\_data + \lambda\, L\_physics$

It can significantly reduce the time cost of thermal hydraulic and structural simulations.

2.6.2 Automatic identification of common design defects

AI can automatically identify the following problems:

- Unconnected pipelines;
- Pipelines with bending radius not meeting specifications;
- Excessively small equipment layout spacing;
- Layout conflicts of components inside the containment;
- Excessively long cable routing.

2.6.3 Design quality risk prediction

Based on data such as design documents, personnel experience, and historical defects, a risk prediction model based on XGBoost or deep learning can be constructed. Input features include professional type, design parameter scale, number of interfaces, etc., and outputs may be:

- High-risk professions;
- High-risk areas;
- High-risk model versions.

This model can be used for early warning to reduce the probability of rework and quality defects.

3 ARTIFICIAL INTELLIGENCE FULL-PROCESS CONTROL SYSTEM FROM THE OWNER'S PERSPECTIVE

During the construction of nuclear power EPC projects, as the leading party, the owner needs to supervise, make decisions, and allocate resources for the entire process of design, procurement, construction, and commissioning. Due to the large number of participating entities, complex information chains, and intertwined risk factors, traditional management models are often difficult to achieve real-time control of large-scale engineering activities. Artificial intelligence technology can improve the owner's management capabilities from three dimensions: data analysis, predictive control, and process supervision, and build an intelligent control system throughout the full life cycle.

Starting from four key links: procurement, construction, quality and safety, and operation and maintenance, this chapter systematically elaborates on the application mechanism and key technical methods of artificial intelligence from the owner's perspective.

3.1 Intelligent Procurement and Supply Chain Management

Nuclear power projects involve a large number of equipment, complex models, multi-level supply chains, and long delivery cycles. The intelligent procurement system can help owners build a transparent, efficient, and controllable supply chain system through demand prediction, supplier evaluation, contract management, and risk monitoring mechanisms.

3.1.1 Procurement demand prediction model

Nuclear power equipment procurement has the characteristics of long cycles and strong coupling. Demand fluctuations are affected by design changes, construction progress, market environment, and other factors. Traditional experience-based prediction methods are difficult to model multiple variables, and the introduction of artificial intelligence can greatly improve prediction accuracy.

The commonly used model is LSTM (Long Short-Term Memory Network), and its core update formulas are as follows (Word linear format):

- Input gate:

$i\_t = \sigma(W\_i\, [h\_(t-1), x\_t] + b\_i)$

- Forget gate:

$f\_t = \sigma(W\_f\, [h\_(t-1), x\_t] + b\_f)$

- Candidate state:

$c{\sim}t = \tanh(W\_c\, [h(t-1), x\_t] + b\_c)$

- Cell state update:

$c\_t = f\_t\, c\_(t-1) + i\_t\, c{\sim}\_t$

- Output gate:

$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$

• Hidden state:

$h_t = o_t \tanh(c_t)$

Based on the above model, the system can make weekly, monthly, and quarterly predictions of equipment procurement demand, identify material shortages, insufficient inventory, and bulk procurement windows in advance, and reduce owner costs.

Prediction results are often used for:

• Formulating annual procurement plans;
• Optimizing equipment batch delivery strategies;
• Judging market price fluctuation trends.

Actual measurements show that the average error of LSTM procurement prediction can be reduced by 40%–60%.

3.1.2 Intelligent supplier evaluation system

The nuclear power supply chain covers thousands of suppliers. Owners need to conduct comprehensive evaluations of their quality, delivery time, cost, technical capabilities, etc. Artificial intelligence can build a supplier evaluation model based on historical data to form a hierarchical management system.

Evaluation indicators can be quantified as feature vectors:

$X = \{ x1, x2, ..., xn \}$

For example:

• x1: Product qualification rate
• x2: On-time delivery rate
• x3: Price rationality
• x4: Service response speed
• x5: Technical capability score

XGBoost is used for classification:

$\hat{y} = F(X) = \sum_{k=1}^{K} f_k(X)$

Where $\hat{y}$ is the supplier grade, such as A/B/C/D.

This evaluation system can support:

• Supplier access;
• Equipment bidding evaluation;
• Designated supply of key equipment;
• Focused monitoring of high-risk suppliers.

Therefore, owners can establish a more transparent and quantifiable supply chain system.

3.1.3 Blockchain-driven intelligent contract management

Nuclear power EPC contracts have complex clauses, long signing chains, and frequent changes. Combining AI with blockchain can build a trusted contract management system[7].

(1) Automatic Contract Review

Clause detection based on natural language processing:

$score_i = match(clause_i, regulation_j)$

If $score_i < threshold$, the system prompts for risky clauses.

(2) Automatic Trigger of Smart Contracts

The workflow of automatic triggering of smart contracts is shown in Figure 4.

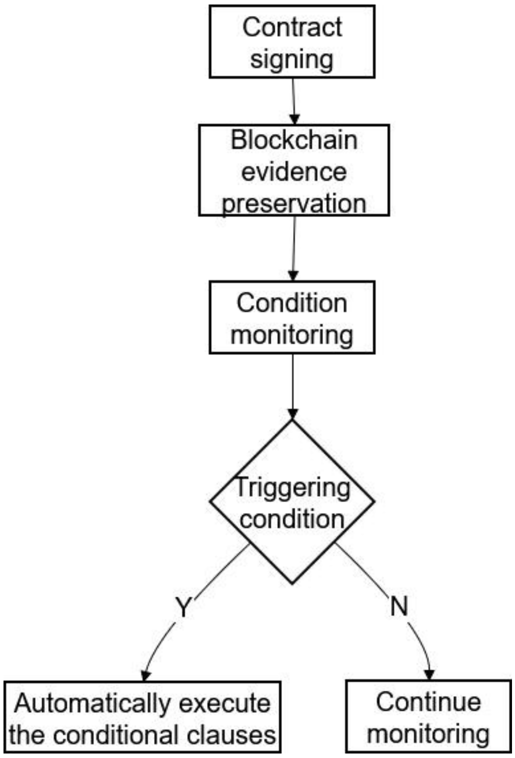

Figure 4 Smart Contracts Automatically Trigger Workflows

Typical automatic trigger events include:
- Automatically initiate acceptance process after equipment delivery;
- Automatically generate risk alerts for overdue delivery;
- Automatically generate payment applications when equipment inspection is qualified.

(3) Supply Chain Risk Early Warning
AI builds a delay probability model based on delivery time, logistics, and quality data:
P(delay) = f(delivery_date, quality_score, logistics_status)
When P(delay) > preset_value, the system issues an early warning.

3.2 Intelligent Monitoring and Progress Prediction in the Construction Stage

The construction stage involves a lot of on-site operations such as civil engineering, installation, and commissioning, and is a key node of nuclear power EPC. AI technology can provide real-time monitoring, automatic analysis, and predictive control capabilities.

3.2.1 Construction progress monitoring based on visual recognition

Deep learning models (such as DeepLabV3+) are used to automatically identify construction entities (concrete, steel bars, equipment, scaffolding, etc.) in on-site photos and videos, and extract their construction status and completion degree.
The specific process is shown in Figure 5.

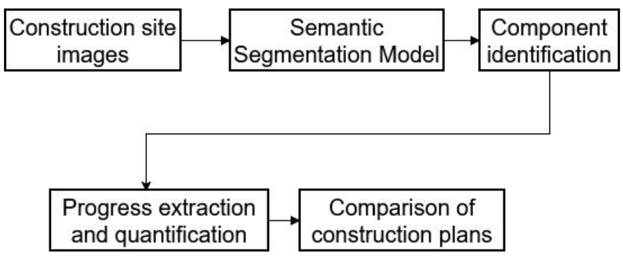

Figure 5 Construction Progress Monitoring Workflow Based on Visual Recognition

The system can automatically generate:
- Completion percentage of single projects;
- Daily completion curve;
- Deviation percentage from the plan.

Quantitative formula:
progress = (actual_completed / planned_total) × 100%

On-site collection frequency can be hourly or even minute-level, allowing owners to timely understand deviation situations.

3.2.2 Progress deviation prediction model

Construction progress is affected by multiple factors such as resource input, weather, and equipment status. A multi-variable prediction model can be established:

$S_{(t+1)} = f(S_t, R_t, W_t, D_t)$

Where:

• S_t: Current progress;
• R_t: Resource input (personnel, equipment);
• W_t: Weather impact factor;
• D_t: Design change situation.

The model can be built based on random forest, LSTM, or Transformer architecture.

Prediction deviation:

$\Delta S = S_{pred} - S_{plan}$

When $|\Delta S| >$ threshold, management measures are automatically triggered.

3.2.3 Reinforcement learning-driven construction scheduling

Construction scheduling can be abstracted as a resource optimization problem. The state space includes equipment, personnel, venues, etc., and the action space includes scheduling, construction sequence, etc.

State update is similar to:

$S_{(t+1)} = g(S_t, A_t)$

Objective function:

$\max R = \sum reward_t$

Reward can be based on:

• Construction period shortening
• Conflict reduction
• Cost saving

Through reinforcement learning, the system can automatically generate efficient scheduling schemes.

3.3 Intelligent System for Quality and Safety Management

Nuclear power engineering has extremely high requirements for quality and safety management, and any defects may lead to serious consequences. AI can empower key links such as detection, identification, and early warning in this field.

3.3.1 Component and weld defect identification

Convolutional Neural Networks (CNN) are used to identify defects in welds, concrete surfaces, and key components[8], such as:

• Cracks
• Holes
• Porosity
• Incomplete welding
• Concrete hollowing

The defect probability can be defined as:

$P(defect) = softmax(W \times feature + b)$

After defect localization, the system automatically generates a quantitative evaluation report.

3.3.2 Safety risk prediction model

Safety incidents are often affected by factors such as operating environment, personnel status, and equipment conditions. A time-series risk prediction model can be constructed:

$Risk\_score = f(worker\_record, equipment\_state, weather, historical\_accidents)$

risk_score is usually normalized to 0–1.

When $risk\_score > 0.7$, the system automatically issues a warning.

3.3.3 VR/AR-driven intelligent safety training

AI can generate immersive safety training courses based on actual construction scenarios, identify workers' operation situations, and score them in real-time. Common indicators include:

• Number of wrong actions
• Proximity to risk sources
• Completion time

System scoring formula:

$score = \alpha \times accuracy + \beta \times time\_eff + \gamma \times safety\_behavior$

This method can significantly improve training effects and reduce on-site safety accidents.

3.4 Intelligent Operation and Maintenance and Predictive Maintenance

The operation and maintenance stage runs through the 60–80-year life cycle of nuclear power plants and is one of the fields where intelligent value is most significant[9].

3.4.1 Equipment health monitoring model

Sensors collect data such as temperature, pressure, vibration, and current to construct health indicators [10]:

HI = f(x1, x2, ..., xn)

Common algorithms include CNN, LSTM, GNN, etc.

3.4.2 Remaining Useful Life Prediction (RUL)

Predict the remaining useful life of equipment based on time-series data:

RUL_pred = g(feature_seq)

RUL is used to guide spare parts replacement and maintenance plans.

3.4.3 Maintenance strategy optimization

Incorporate maintenance costs and failure losses into the total cost model:

C_total = C_maint + P(failure) × C_failure

Through optimization:

min C_total

The system can automatically give the optimal maintenance cycle.

4 AI-ENABLED FULL-PROCESS COLLABORATIVE PLATFORM ARCHITECTURE

The full process of nuclear power EPC spans 8–10 years, with extremely complex data types, including multi-modal information such as design data, procurement data, on-site construction data, and operation and maintenance monitoring data. To realize the collaborative application of artificial intelligence in the full process, a unified technical platform must be built to achieve closed-loop collaborative management of design, procurement, construction, and operation and maintenance through data connection, model collaboration, and system integration. The architecture proposed in this chapter integrates cloud computing, edge computing, Internet of Things, artificial intelligence, and digital twin technologies, referring to the research results of domestic and foreign digital twin platforms [4, 9], to build a system foundation with high reliability, scalability, and evolvability for nuclear power EPC projects.

4.1 Overall Platform Architecture Design

Nuclear power projects have extremely high requirements for data security, system reliability, and real-time performance. Therefore, the platform architecture needs to meet the engineering characteristics of "controllable, traceable, and verifiable". The architecture proposed in this study adopts a "cloud-edge-end" three-tier collaborative system.

4.1.1 Overall Architecture Layering

The overall structure of the platform is shown in Figure 6.

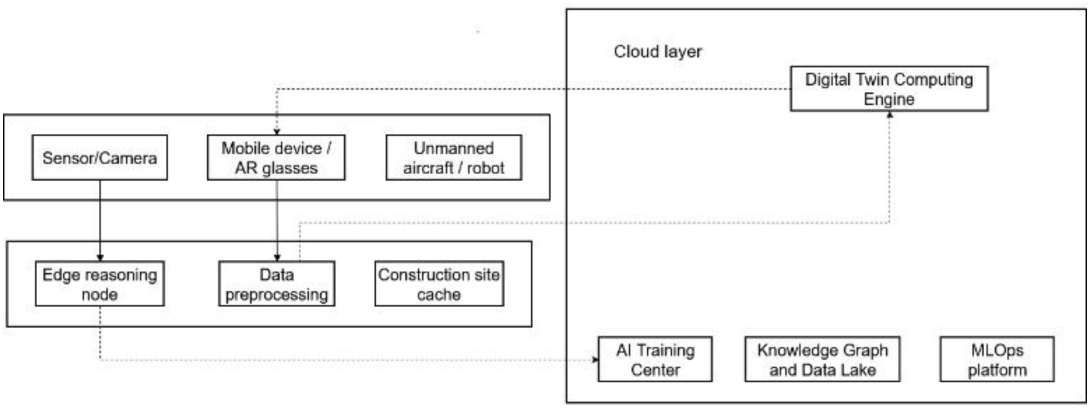

Figure 6 Overall Platform Architecture

The three layers operate collaboratively, among which:

- The Device layer is responsible for data collection;
- The Edge layer is responsible for real-time inference and rapid response;
- The Cloud layer is responsible for training, analysis, modeling, and global collaboration.

This enables the platform to have both real-time performance and strong computing capabilities, meeting the business needs of nuclear power sites.

4.1.2 Data lake and data governance system

The nuclear power EPC platform needs to process structured, semi-structured, and unstructured data, including:

- CAD/BIM models
- Construction images and videos
- Equipment operation time-series data

• Text reports and contract clauses
• Procurement and supply chain data
The data lake adopts a distributed storage structure, such as MinIO, HDFS, or object storage. Data is organized by subject area, such as:
• Design domain
• Procurement domain
• Construction domain
• Operation and maintenance domain
Data governance adopts a Master Data Management (MDM) system, with core including:
• Data standard formulation
• Data quality control
• Metadata management
• Cross-subject sharing mechanism
Data processing usually follows the following process:
Raw Data -> Cleaning -> Transformation -> Feature Extraction -> Model Input
The platform is designed to ensure that data from different sources can be correlated and analyzed in real-time.

4.2 MLOps-Driven Model Lifecycle Management

AI models used in nuclear power engineering include various types such as visual models, predictive models, optimization models, and semantic models. They are large in quantity and updated frequently, and must be managed uniformly by the MLOps (Machine Learning Operations) system.
4.2.1 Model training and automatic deployment
The MLOps management process is shown in Figure 7.

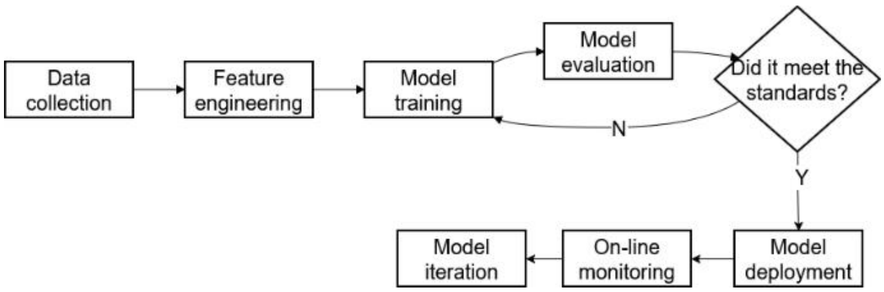

Figure 7 MLOps Management Process

Feature engineering includes:
• Feature Selection
• Normalization
• Encoding
• Windowing
Model deployment adopts containerization, combined with tools such as Kubernetes and Docker to achieve automatic scaling and gray release.
4.2.2 Model version management and traceability
Model version structure:
$Model\_v(t) = Hash(Model\_(t-1) \| \Delta\_params \| \Delta\_data)$
Where:
• Δ_params represents parameter updates;
• Δ_data represents changes in training data.
It realizes the full-life-cycle auditability of models, which is applicable to the review and compliance requirements of the nuclear power field.
4.2.3 Model monitoring and degradation detection
Online monitoring indicators include:
• Accuracy
• Latency
• Confidence Drift
• Data Drift
For predictive models, distribution drift can be measured by KL divergence:
$D\_KL(P \| Q) = \sum P(x) \times \log(P(x) / Q(x))$
When the drift exceeds the threshold, the platform will automatically:
• Trigger model retraining;
• Switch to standby models;

• Degrade operation.
Ensure the reliability of models in nuclear power safety scenarios.

4.3 Digital Twin Platform and Intelligent Scenario Construction

Digital twin technology is the core cornerstone of nuclear power EPC intelligence[10]. It forms a real-time interactive virtual-real fusion system by integrating physical models, data models, and AI models.

4.3.1 Digital twin construction method

The twin system consists of three parts:
1. Physical Entity: Nuclear island, conventional island, plant, equipment, etc.
2. Virtual Model: 3D models, calculation models, behavior models
3. Data Link: Real-time data from sensors, construction sites, and operation and maintenance systems

Twin state update:
State_t = f(Sensor_t, Model_t, Control_t)
The twin system can realize:
• Real-time monitoring
• Behavior prediction
• Working condition simulation
• Decision optimization

4.3.2 3D model-driven construction simulation

Twin models based on BIM/point clouds can support:
• Construction process simulation
• Dynamic collision detection
• Safety risk analysis
• Construction path optimization

Real-time mapping of construction progress:
Progress_3D = Map(Progress_actual)
Enable managers to intuitively see progress deviations in 3D space.

4.3.3 Digital twin-driven operation optimization

In the operation and maintenance scenario, the twin model can realize predictive analysis through time-series data and physical constraints [8]:
Prediction = g(Sensor_seq, Physics_rules)
Typical functions include:
• Temperature and pressure anomaly prediction
• Equipment life prediction
• Fault propagation path simulation
• Optimal maintenance strategy generation

The operation delay of the twin system can be controlled within 300–500 ms, meeting the real-time requirements of nuclear power scenarios.

4.4 Cloud-Edge-End Collaborative Mechanism

Nuclear power project construction sites have serious signal occlusion and large network fluctuations. A cloud-edge-end collaborative method must be adopted to ensure the real-time performance and stability of the system.

4.4.1 Edge inference mechanism

Edge nodes execute lightweight models, such as YOLO-Lite and MobileNet, for:
• Real-time detection on construction sites
• Safety behavior identification
• Image quality preliminary screening

Edge inference results:
Result_edge = Infer(Model_edge, Input)
Results can be generated in milliseconds.

4.4.2 Cloud-based centralized training mechanism

The cloud executes high-computing-power tasks, including:
• Large model training
• Twin model calculation
• Global optimization scheduling
• Massive data analysis

The cloud model serves as the main model:
Model_cloud = Train(Data_all)
And regularly pushes updates to edge nodes.

4.4.3 Collaborative operation and model synchronization

Through the parameter synchronization mechanism:
$\theta\_edge(t+1) = \alpha \times \theta\_cloud(t) + (1 - \alpha) \times \theta\_edge(t)$
Realize the fusion between edge and cloud models.

4.5 System Security and Compliance Requirements

The nuclear power industry has extremely high requirements for system security. The platform design meets:

- Hierarchical data protection
- User permission control
- Full-process operation audit
- Model decision interpretability
- Compliance with nuclear safety software review processes

Build a "controllable, verifiable, and trusted" intelligent collaborative platform.

5 APPLICATION CASES AND BENEFIT ANALYSIS

To verify the effectiveness of the artificial intelligence-enabled nuclear power EPC full-process collaborative management system, this chapter selects typical nuclear power engineering projects for application research, and evaluates the application effects from four stages: design, procurement, construction, and operation and maintenance. Meanwhile, a comprehensive evaluation model including economic benefits, quality benefits, construction period benefits, and safety benefits is constructed to systematically analyze the engineering value of the platform. The content of this chapter aims to prove the feasibility, advancement, and promotion value of the aforementioned technical system through engineering practice.

5.1 Typical Nuclear Power Engineering Intelligent Application Cases

This study selects three representative nuclear power engineering scenarios in China as cases, namely the Phase I Project of a 1 million kilowatt-class pressurized water reactor nuclear power plant (Case A), a large-scale Generation III nuclear power technology demonstration project (Case B), and the intelligent operation and maintenance system of a high-temperature reactor demonstration project (Case C). These projects cover different construction stages and business scenarios and have strong representativeness.

5.1.1 Case A: application of intelligent design system in nuclear power design institutes

Case A selects the conventional island design stage of a 1 million kilowatt-class nuclear power project, and introduces an intelligent parametric design, intelligent review, and knowledge graph collaborative platform to solve the problems of long design cycles, low professional collaboration efficiency, and high review costs.
(1) Significant Improvement in Intelligent Parametric Design Efficiency
After adopting the intelligent design model, the generation time of equipment layout schemes is shortened from 3–5 days to several minutes. The optimization process is as follows:
$T\_reduction = (T\_manual - T\_AI) / T\_manual \times 100\%$
Calculated with actual data:
$T\_manual = 72$ hours
$T\_AI = 0.5$ hours
Substitute:
$T\_reduction = (72 - 0.5) / 72 \times 100\% \approx 99.3\%$
It shows that AI significantly shortens the design generation time.
(2) Improved Accuracy of Automatic Specification Review
The intelligent specification review system covers 3,000 constraint conditions, with a review accuracy of over 95%, effectively reducing manual review omissions, especially in cross-reviews of structural, electrical, and other professions.
(3) Reduction of Multi-Professional Conflicts
After adopting semantic association + collision detection technology, the number of identified model conflicts has decreased significantly. The statistics are as follows:

- Conflict quantity decreased by about 70%
- Conflict localization speed increased by 200%
- Conflict rectification cycle shortened by more than 40%

These results indicate that AI can well support the collaborative optimization of the nuclear power design stage.

5.1.2 Case B: application of intelligent procurement system in large-scale nuclear power construction projects

Case B selects a large-scale Generation III nuclear power project, covering thousands of equipment suppliers, hundreds of thousands of items, and thousands of contracts. By building an intelligent supply chain system, it realizes procurement demand prediction, supplier evaluation, and contract risk monitoring.
(1) Significant Reduction in Procurement Prediction Errors
The LSTM model is used to predict equipment procurement demand, and the prediction error (MAPE) is as follows:
$MAPE = (1/n) \times \sum | (y\_pred - y\_real) / y\_real |$

Actual data shows that the prediction error of the AI model has decreased from 18% to 6%, and the prediction accuracy has nearly tripled.
(2) Intelligent Hierarchical Management of Suppliers
The XGBoost model scores based on more than 30 evaluation indicators, forming:
• Grade A suppliers: Stable and reliable
• Grade B suppliers: Basically meet requirements
• Grade C suppliers: Have unstable factors
• Grade D suppliers: High risk
The model prediction accuracy reaches 92%, which is about 20% higher than the manual experience method.
(3) Contract Risk Identification and Early Warning
The intelligent contract system judges performance risks based on node data such as logistics, quality inspection, and document delivery. When the delay probability:
$P(delay) > 0.6$
The system automatically issues an early warning.
In actual projects, more than 40 major delay risks were successfully identified at an early stage, greatly reducing breach of contract losses.
5.1.3 Case C: application of intelligent operation and maintenance system in demonstration projects
The high-temperature gas-cooled reactor demonstration project uses an intelligent operation and maintenance system to realize equipment health monitoring, fault prediction, and maintenance strategy optimization[6].
(1) Equipment Remaining Useful Life Prediction (RUL)
Modeling based on CNN-LSTM:
$RUL\_pred = g(feature\_seq)$
Actual deployment shows:
• The prediction error of key equipment is controlled within ±10 days
• The early fault identification rate reaches 87%
(2) Maintenance Strategy Optimization
Operation and maintenance cost model:
$C\_total = C\_maint + P(failure) \times C\_failure$
After the system automatically recommends maintenance plans:
• Unplanned downtime reduced by 80%
• Annual operation and maintenance costs decreased by 18%–25%
(3) Digital Twin-Driven Operation Simulation
The digital twin can real-time simulate equipment operation conditions [5], supporting:
• Thermal hydraulic behavior analysis
• Anomaly propagation path simulation
• Working condition switching risk assessment
The delay is controlled within 400–500 ms, fully meeting the operation business requirements.

5.2 Benefit Analysis and Quantitative Evaluation

To uniformly evaluate the value of the artificial intelligence system in the full process of nuclear power EPC, this section constructs a comprehensive benefit analysis system, including four dimensions: economic benefits, quality benefits, construction period benefits, and safety benefits.
5.2.1 Economic benefits
Economic benefits come from:
(1) Labor cost savings
(2) Reduction of rework
(3) Reduction of material loss
(4) Reduction of equipment maintenance costs
Economic benefit model:
$E\_total = E\_labor + E\_rework + E\_material + E\_maint$
A typical nuclear power project saves about 200–500 million yuan in overall costs.
5.2.2 Quality benefits
Quality improvement is mainly reflected in:
• Reduction of design errors
• Stable quality of equipment procurement
• Reduction of construction defects
• Significant improvement of operation and maintenance reliability
Design error reduction rate:
$Q\_improve = (Q\_before - Q\_after) / Q\_before \times 100\%$
In actual projects, the quality improvement range is 30%–50%.
5.2.3 Construction period benefits

Relying on intelligent monitoring and predictive control in the construction stage can reduce progress deviations:
• Key path deviation reduction: 20–40%
• Rework rate reduction: 30–60%
• Construction period shortening: 3–10 months (depending on project scale)
Construction period saving model:
T_saved = T_plan - T_actual
A large-scale project saved 280 days of construction period.

5.2.4 Safety benefits

Safety benefits are prominently reflected in:
• Dangerous behavior identification rate higher than 95%
• Risk prediction accuracy >80%
• Major accident reduction ratio: more than 50%
The safety factor improvement model can be defined as:
S_gain = (Incidents_before - Incidents_after) / Incidents_before
The number of safety accidents in multiple demonstration projects shows a significant downward trend.

5.3 Comprehensive Benefit Model and Evaluation Results

Construct a comprehensive benefit scoring model:
Score_total = $\alpha \times E + \beta \times Q + \gamma \times T + \delta \times S$
Where:
• E: Economic benefit score
• Q: Quality benefit score
• T: Construction period benefit score
• S: Safety benefit score
Empirical values:
• $\alpha = 0.35$
• $\beta = 0.25$
• $\gamma = 0.25$
• $\delta = 0.15$
Evaluation results show that the comprehensive score of the AI-enabled EPC platform is more than 45%–70% higher than that of the traditional system, reflecting significant engineering value and industry promotion potential.

6 CONCLUSIONS AND PROSPECTS

Nuclear power EPC engineering is a typical large-scale construction project with high complexity, high safety level, and multi-stakeholder collaboration. The entire process of these projects covers four key stages: design, procurement, construction, and operation and maintenance, involving a large number of data interactions, professional couplings, and management decisions. Under the traditional model, due to problems such as information silos, inconsistent professional interfaces, opaque supply chains, lagging construction monitoring, and high operation and maintenance costs, nuclear power engineering management has long faced problems of low efficiency, high risks, and frequent rework. This study conducts a systematic discussion around artificial intelligence empowering nuclear power EPC full-process collaborative management, and proposes an engineering implementable technical system and verification plan, forming the following conclusions.

6.1 Research Conclusions

(1) Constructed the Overall Theoretical Framework for Intelligent Management of Nuclear Power EPC Full Process
The paper constructs a management system of "data connection - scenario modeling - algorithm driving - platform integration", realizing a unified logical framework from design to operation and maintenance. Through the integration of cloud-edge-end collaborative architecture, knowledge graph system, and digital twin structure, it realizes the systematic, model-based, and intelligent management of the full life cycle of nuclear power, providing a methodological foundation for subsequent engineering practice.
(2) Formed an Intelligent Design Technology System for Design Institutes
An intelligent design system based on parametric design, generative models, intelligent specification review, multi-professional collaboration, and semantically enhanced collision detection is proposed. Research shows that:
• Parametric design increases design generation efficiency by about 95%–99%;
• The accuracy of intelligent specification review exceeds 95%, significantly reducing manual review costs;
• The identification rate and localization speed of multi-professional conflicts are greatly improved, and overall conflicts are reduced by about 70%.
This system can effectively improve design quality, reduce rework, and accelerate design iterations.
(3) Formed Intelligent Procurement, Construction, and Operation and Maintenance Models from the Owner's Perspective

Through technologies such as LSTM procurement prediction model, intelligent supplier evaluation model, and contract risk early warning system, it realizes predictable, monitorable, and quantifiable management of procurement behaviors; through visual recognition, progress prediction, and reinforcement learning scheduling models, it realizes digital monitoring and dynamic optimization of the construction stage; through equipment health monitoring, remaining useful life prediction (RUL), and optimized maintenance strategy models, it realizes intelligent auxiliary decision-making in the operation and maintenance stage. Practical applications show that:

- Procurement prediction error is reduced to 1/3 of the original;
- The real-time performance of construction deviation identification is improved to minute-level;
- Fault prediction accuracy is increased to over 80%;
- Equipment downtime is reduced by more than 50%.

(4) Constructed a Full-Process Collaborative Platform with Engineering Capabilities

The cloud-edge-end integrated platform proposed in the paper realizes the automatic management of the full life cycle of models through the MLOps management mechanism; the data lake system realizes the management and sharing of massive data; the digital twin platform realizes the real-time mapping of construction sites and unit operations. The platform meets the industry requirements of high safety, strong reliability, and auditability of nuclear power engineering, and has engineering application capabilities.

(5) Verified the Feasibility and Value of the Technical System Through Typical Cases

Three typical nuclear power engineering cases (design, construction, operation and maintenance) show that the intelligent system proposed in this study can bring significant benefits in terms of cost, quality, efficiency, safety, etc.:

- Cost reduction: 200–500 million yuan
- Construction period shortening: 3–10 months
- Defect reduction: 30%–60%
- Improved operational reliability: equipment availability > 98%

The comprehensive benefit score is increased by 45%–70%.

6.2 Research Innovations

The main innovations of this study include:

(1) Proposed a full-process collaborative AI architecture for nuclear power EPC, realizing the full-process intelligent connection of design, procurement, construction, and operation and maintenance;

(2) Constructed a knowledge graph system for nuclear power multi-professional collaboration, realizing the intellectualization of specification review, interface management, and model conflict checking;

(3) Innovatively integrated deep learning, reinforcement learning, and digital twin technologies into nuclear power construction management [1, 10], realizing a closed loop from perception, analysis to prediction and decision-making;

(4) Proposed a nuclear power engineering MLOps system with cloud-edge-end collaboration, realizing a traceable, reliable, and controllable management mechanism for the full life cycle of models.

6.3 Prospects

Although this study has formed a relatively complete nuclear power EPC AI management system, with the development of new nuclear power technologies and new devices, there is still room for further research. Future research can be deepened in the following directions:

(1) Building larger-scale industry-level pre-trained large models

Including nuclear power structure models, nuclear safety multi-modal models, and construction behavior recognition models to improve cross-scenario transfer capabilities.

(2) Constructing a more secure and reliable trusted AI technical system

Involving model interpretability (Explainable AI), trusted reasoning, model robustness, anti-attack capabilities, etc., to provide higher standard support for nuclear power industry safety supervision.

(3) Deepening the deep integration of digital twins and physical field simulation

Making the twin system not only static visualization but also a dynamic simulation tool with real-time solution capabilities.

(4) Exploring the application of AI in new nuclear power construction models

Including modular construction, automatic welding, on-site robot inspection, etc., to promote the development of intelligent construction systems.

(5) Constructing a full-process data standard system for nuclear power EPC

Formulating unified data models, interface specifications, and data sharing protocols to promote data interoperability and system interconnection at the industry level.

In general, the development of artificial intelligence empowering nuclear power EPC is still in an accelerated stage. In the future, it will further move towards intelligence, autonomy, and collaboration, forming a more intelligent, efficient, and safe nuclear power engineering construction and management model.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Farber J, Kobayashi K, Alajo A, et al. Integration of Control Methods and Digital Twins for Advanced Nuclear Reactors. Idaho National Laboratory (INL) / U.S. DOE, 2025.
[2] Kropaczek D J, Badalassi V, Jain P K, et al. Digital Twins for Nuclear Power Plants and Facilities// in Nuclear Engineering Handbook. Springer, 2023.
[3] U.S. Nuclear Regulatory Commission. NRC Research Activities for Nuclear Digital Twins. Washington, D.C.: NRC, 2024.
[4] Zhang X, Chen Y, Li Q, et al. Intelligent Design and Construction Coordination of Nuclear Power Based on Digital Twin// Proceedings of GEESD 2022. IOS Press, 2022: 276.
[5] Xing Y J, Li W Z, Zhang C D. Research on the Application of 3D Digital Twin Technology in Nuclear Power Engineering Construction. China Science and Technology Information, 2022(19): 45-50.
[6] Wu L, Liu Y S, Xue X, et al. Application of Grid Safety Management Model in Smart Construction Site of Nuclear Power Engineering. China Nuclear Power, 2024(6): 764–768.
[7] Do Y, Zebrowitz M, Stahl J, et al. iFANnpp: Nuclear power plant digital twin for robots and autonomous intelligence. Annals of Nuclear Energy, 2025: 111993.
[8] Daniell J, Kobayashi K, Alajo A, et al. Digital twin-centered hybrid data-driven multi-stage deep learning framework for enhanced nuclear reactor power prediction. arXiv:2211.13157, 2022.
[9] Hu M, Zhang X, Peng C, et al. Current status of digital twin architecture and application in nuclear energy field. Annals of Nuclear Energy, 2024: 110491.
[10] Hossain R B, Ahmed F, Kobayashi K, et al. Virtual sensing-enabled digital twin framework for real-time monitoring of nuclear systems leveraging deep neural operators. arXiv:2410.13762, 2024.