Proceedings of the 4th International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/2026.34961

# AI and Digital Twin–Driven Intelligent Management and Control for Green Transformation of Process Equipment under China's Dual Carbon Goals

**Weixuan Luo**

*Institute of Problem Solving, Hefei University of Technology, Hefei, China*
*weixuanluo0805@163.com*

***Abstract.*** The Dual Carbon goals (carbon peak by 2030, carbon neutrality by 2060) impose systematic green transformation requirements on high-energy-consumption and high-emission process industries such as petrochemicals, power, and metallurgy. However, the energy consumption and emissions of process equipment are characterized by strong operating condition disturbances, significant nonlinearity, and difficulty in cross-level data integration, making it challenging for traditional empirical control methods to achieve "real-time — predictive — optimized — closed-loop" energy saving and carbon reduction. Based on a research framework integrating AI and digital twins, this paper proposes an intelligent management and control pathway for process equipment and control engineering, from data acquisition to the establishment of an integrated energy-carbon management platform. Digital twins are applied to achieve equipment online health monitoring, while AI is used to achieve energy efficiency prediction and optimization control. In addition, a full-process traceable carbon management platform is building to analyze challenges in data governance, model interpretability and safety, engineering deployment costs, and talent. Furthermore, this paper proposes several policies and technical recommendations, including advancing industrial AI energy efficiency management system standards, developing Physics-Informed Neural Networks (PINN) to enhance model extrapolation safety, promoting open-shared digital twin model libraries and typical datasets, and improving university-enterprise collaborative talent cultivation systems. The research provides a reference for the intelligent upgrading of green factories and energy-saving equipment.

***Keywords:*** Dual Carbon, Process Equipment, Green Transformation, Digital Twin, Industrial AI

## 1. Introduction

The Dual Carbon goals provide a clear timetable and hard constraints for the green transformation of process industries. Unlike simple end-of-pipe treatment, carbon emissions in process industries are highly coupled with energy efficiency levels. They are often jointly determined by equipment selection, process scheduling, operational control, and maintenance strategies. Therefore, the key to

DOI: 10.54254/2755-2721/2026.34961

green transformation is to realize the intelligent operation of process equipment, including perception, prediction ability, optimization ability and sense of responsibility [1].

At present, the intelligent management and control of process equipment face three major problems. The first problem is the poor quality of on-site data and system fragmentation. There are data silos between DCS, MES, ERP and carbon accounting systems, and their calibration inconsistency limits digital twin modeling and calibration [1]. The second problem is that the reliability and security of the model are poor. When the operating conditions change significantly, most AI methods become less interpretable due to generalization and insufficient physical restrictions, so it is difficult to meet the safety requirements of the control system [2]. The third question needs to pay attention to the project cost and talent gap. The application of digital twin requires hardware, software and multidisciplinary teamwork, which is very difficult for small and medium-sized enterprises.

In this case, the combination of AI and digital twins provides a technical way for green intelligent management and control. Digital twins can support online monitoring and diagnosis through high-fidelity mapping, while AI can improve energy efficiency through data-driven prediction and optimization. In addition, an integrated energy-carbon platform can integrate energy consumption and emissions into the same closed-loop decision-making, which provides an effective tool for quantification and traceability for carbon management.

## 2. AI and Digital Twin-driven intelligent management and control of process equipment: core performance and technical architecture

### 2.1. Digital Twin-driven real-time energy efficiency monitoring and diagnosis

Digital Twin (DT) is a virtual representation of physical equipment constructed from real-time sensor data, historical data, and physics-based models. It enables visualization of operational status, health diagnosis, and performance evaluation [2]. Although a digital twin can integrate AI components, e.g., machine learning models, to enhance predictive and analytical capabilities, its core purpose is to establish a "state–mechanism–result" closed-loop mapping, thereby providing mechanistic explanations and root-cause analysis of anomalies. In contrast, Artificial Intelligence (AI) in energy efficiency optimization focuses on modeling complex nonlinear relationships, predicting key performance indicators, and generating optimal control strategies. AI emphasizes the "prediction–decision–closed-loop optimization" process, leveraging historical and real-time data to improve energy efficiency and reduce losses. Therefore, DT and AI play complementary roles in intelligent process equipment management. Digital twins supply high-quality state information and physical constraints that serve as the foundation for AI-based optimization control, while AI uses these data to generate predictive insights and control strategies. In other words, digital twins emphasize equipment status and mechanism explanation, whereas AI emphasizes energy efficiency optimization and decision-making. Together, they enable intelligent management of process equipment in green factories [3].

Key state variables of process equipment, such as compressors, cracking furnaces, electrolytic cells, etc. include temperature, pressure, flow rate, vibration, energy consumption, and operating condition parameters. By establishing digital twin models, real-time sensor data can be coupled with the physical mechanisms of equipment to achieve equipment online health checks. In this framework, digital twins are used not only for operational status visualization, but also for identifying root causes of energy efficiency degradation, such as decreased heat transfer coefficients, abnormal valve throttling, and efficiency losses caused by rotor vibration. This capability provides

DOI: 10.54254/2755-2721/2026.34961

the foundation of green transformation that by identifying the sources of energy efficiency losses solely can optimize control to achieve targets and objective functions.

Compared with traditional monitoring approaches, digital twins have the advantage of state-mechanism-result correlation, elevating anomaly warnings from threshold alarms to mechanism explanation and impact assessment. Related research on the digitalization, networking, and intelligentization of the full process of low-carbon industrial production provides directional references for data integration and intelligentization from equipment to the entire process [3].

### 2.2. AI-driven energy efficiency optimization control: prediction—decision—closed loop

In green factory practice, the value of energy efficiency control lies in directly reducing comprehensive energy consumption and reducing hidden losses, such as overload operation, ineffective energy consumption, frequent start-stops, etc. At the same time, for engineering deployment, control strategies need to balance safety constraints and robustness, thereby avoiding control risks brought by black-box strategies [4, 5].

Green transformation requires not only diagnosis, but also optimization. Control methods based on deep learning or reinforcement learning can minimize the energy consumption of unit products while meeting production restrictions. First, by using time series models, such as transformer-based architecture, to learn the operating condition-energy consumption mapping relationship, energy consumption and key variable predictions can be realized, so as to obtain predictions that can be used for control [6]. Secondly, constraint optimization and dynamic search are carried out within the scope of operating variables such as feed rate, speed and valve opening. Third, closed-loop feedback and strategy update are realized through the controller's execution of optimization results and the continuous correction of the prediction model with new data.

In the practice of green factories, the value of energy efficiency control lies in directly reducing comprehensive energy consumption and reducing hidden dangers, such as overload operation, low efficiency consumption, frequent start-up and stop, etc. At the same time, for engineering deployment, the control strategy needs to balance security constraints and robustness, so as to avoid the control risks brought about by the black box strategy [4, 5].

### 2.3. Integrated energy-carbon management platform: dual-control dashboard from energy consumption to carbon emissions

The relationship between energy efficiency and carbon emissions is not simply linear, especially when factors such as power structure, fuel ratio, and process by-products change [7]. Therefore, it is necessary to build an integrated energy-carbon management platform by integrating SCADA/edge data, digital twin calculation results, and carbon emission factor databases to form an "energy + carbon emissions" dual-control dashboard. Through this framework, it can achieve real-time calculation of energy consumption and carbon emissions, traceability of key carbon emission influencing factors, and dual-objective trade-off of optimization strategies, e.g., minimum energy consumption + minimum carbon intensity / compliance constraints) [4].

Related research on digital twin-driven green development provides support for enterprises to build multi-dimensional indicator integrated platforms. In addition, studies on carbon trading and digital twin applications in the coal industry provide references for the operational logic of "carbon emissions as quantifiable assets".

DOI: 10.54254/2755-2721/2026.34961

## 3. Analysis of transformation drivers: triple drivers of policy, economy, and technology

### 3.1. Policy drivers: hard constraints and standardization orientation

The Dual Carbon goals create continuous constraints and incentives for process industries through industry implementation plans, energy efficiency benchmark requirements, and energy-saving equipment renewal policies. These policy mechanisms are manifested as strengthening assessment indicators for energy efficiency and emissions, promoting evaluation systems for green factories and green supply chains, and facilitating smart factory construction through digital transformation guidelines. Therefore, the value of "AI + digital twins" lies not only in technological advancement, but also in its capability to transform compliance goals into computable, optimizable, and auditable engineering capabilities [8].

### 3.2. Economic drivers: dual pressure of energy costs and carbon costs

Continuous fluctuations in energy costs have made energy saving and consumption reduction core means for enterprises to reduce costs. Meanwhile, carbon trading mechanisms have given carbon emission rights quantifiable attributes, forcing enterprises to manage emissions in a more refined manner. In this context, AI energy efficiency optimization can reduce comprehensive energy consumption and improve equipment operating efficiency, while integrated energy-carbon platforms further improve carbon accounting accuracy and compliance efficiency.

### 3.3. Technology drivers: maturity of data acquisition, AI algorithms, and digital twin platforms

The rapid development of IoT and 5G has improved real-time field data acquisition capabilities. At the same time, AI algorithms, such as deep learning and deep reinforcement learning are better at handling high-dimensional nonlinear processes. In addition, cloud and digital twin platforms have lowered the barriers to modeling and deployment. Technical frameworks and digital twin taxonomies proposed in related research provide methodological references for building systematic paths of engineering-data-model.

## 4. Potential issues and challenges: from technical reliability to engineering sustainability

### 4.1. Data quality and governance challenges: from "usable data" to "available data"

Process equipment data has issues of noise, missing values, inconsistent sampling frequencies, and calibration differences. More critically, cross-system data silos lead to several problems, including increased difficulty in calibrating digital twin models, incomplete links in energy efficiency and carbon emission accounting, and the lack of a stable training foundation for AI optimization decisions.

Therefore, it is necessary to establish unified data governance and data interface specifications, including data cleaning, time-series alignment, feature standardization, and consistency of carbon factors and accounting calibration.

DOI: 10.54254/2755-2721/2026.34961

### 4.2. Insufficient model generalization and interpretability: safety risks under changing operating conditions

AI models often have black-box characteristics and may fail under new operating conditions or even output unsafe control instructions when lacking physical constraints. Similarly, digital twins that rely solely on data fitting without physical consistency may also reduce credibility.

### 4.3. Investment costs and talent gaps: practical constraints for deployment

The deployment of digital twins and industrial AI typically involves sensor upgrades, edge computing power, platform software, data governance and algorithm iteration, and the need for composite talent teams. As a result, small and medium enterprises find it harder to access funding and talent. Therefore, it is necessary to develop modular, low-cost, progressively upgradeable engineering routes.

## 5. Future policy recommendations and optimization directions

### 5.1. Policy level: special funds, standard interfaces, and evaluation system linkage

It is recommended to establish special funds for intelligent and green process equipment to focus support on small and medium enterprises in carrying out digital twin pilots and platform construction. In addition, technical specifications for industrial AI energy efficiency management systems should be developed to form unified data interfaces and interoperability standards to reduce system integration costs. Furthermore, AI energy efficiency management capabilities should be incorporated into green factory and green supply chain evaluation indicator systems to strengthen market-driven forces.

### 5.2. Technology R&D level: physics-information fusion and edge low-latency control

Methods such as Physics-Informed Neural Networks (PINN) should be developed to enhance model extrapolation capability and safety. For engineering deployment, develop low-cost, modular edge intelligent controllers to achieve local data processing and low-latency control, reducing cloud dependency and network risks. In addition, building open-shared process equipment digital twin model libraries and typical process datasets would help promote cross-industry migration and reuse.

Based on the research framework of intelligent operation and maintenance systems for high-end equipment based on digital twins, these approaches provide a systematic approach for equipment-level digital twins to move from operation and maintenance to green transformation. Meanwhile, related research on digital twin-driven green development can provide references for regional-level practical paths.

### 5.3. Talent cultivation level: curriculum system and university-enterprise collaborative laboratories

Core courses such as Industrial AI and Digital Twin Technology should be added to process equipment and control engineering programs. Universities and enterprise should establish joint laboratories to carry out "AI + process equipment" practical training projects. Through the closed-loop cultivation of engineering scenario-model training-control verification, it will be possible to

DOI: 10.54254/2755-2721/2026.34961

develop composite talents to solve the structural shortage of people who understand processes, control, and AI.

## 6. Conclusion

The Dual Carbon goals have placed new requirements on process equipment and control engineering, shifting the focus from energy efficiency improvement and emission compliance to intelligent management and sustainable operation. The integration of AI and digital twins provides a systematic pathway for achieving green transformation. Digital twins are used for equipment online monitoring and mechanism diagnosis, while AI is applied to energy efficiency prediction and constrained optimization control. In addition, integrated energy-carbon platforms make the carbon emissions to be traceable, auditable, and optimizable. This paper reviews the performance and causes of transformation, pointing out challenges in data governance, model generalization and safety, costs, and talent. Looking ahead, coordinated progress through policy guidance, technological breakthroughs, standard interface construction, and talent cultivation should form a safe, efficient, and low-carbon intelligent process equipment system. Such efforts will further support the process industry in maintaining competitiveness under the Dual Carbon goals.

## References

[1] Alnowaiser, K. K., & Ahmed, M. A. (2022). Digital Twin: Current Research Trends and Future Directions. Arabian Journal for Science and Engineering, 48(2), 1075–1095.

[2] Mohanraj, R., & Vaishnavi, B. K. (2025). Data enabling technology in digital twin and its frameworks in different industrial applications. Journal of Industrial Information Integration, 44, 100793.

[3] Liu, H., Chen, X., Hu, Y., Cheng, B., & Skibniewski, M. J. (2026). Systematic integration and quantitative benchmarking of digital technologies empowering low carbon building: a three-dimensional analytical framework. Energy and Buildings, 361, 117490.

[4] Yu, W., Patros, P., Young, B., Klinac, E., & Walmsley, T. G. (2022). Energy digital twin technology for industrial energy management: Classification, challenges and future. Renewable and Sustainable Energy Reviews, 161, 112407.

[5] Ghenai, C., Husein, L. A., Al Nahlawi, M., Hamid, A. K., & Bettayeb, M. (2022). Recent trends of digital twin technologies in the energy sector: A comprehensive review. Sustainable Energy Technologies and Assessments, 54, 102837.

[6] de Larmelina, S., da Silva, A. L., & Risso, L. A. (2025). Conceptualizing the Digital Twin: An Analysis of Definitions, Applications, Technologies, Benefits and Challenges. Journal of Advanced Manufacturing Systems, 25(02), 253–279.

[7] Chen, C., Zhao, Z., Xiao, J., & Tiong, R. (2021). A Conceptual Framework for Estimating Building Embodied Carbon Based on Digital Twin Technology and Life Cycle Assessment. Sustainability, 13(24), 13875.

[8] Zhai, T., Qian, F., Guan, X., Ding, J., Du, W., Xu, Z., Yang, T., Liu, K., He, J., Song, S., Zhao, R., Wang, Z., & Liu, Y. (2024). Theories and technologies of automation and intelligence for carbon peak and carbon neutrality. Bulletin of National Natural Science Foundation of China, 38(4), 560-570.