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Self-Evolutionary Optimization of Wide-Load Thermal Control Systems for Coal-Fired Power Units Driven by Digital Twins

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Abstract: Under the "dual-carbon" goals, the construction of a new power system imposes requirements for deep peak regulation and flexible operation on conventional coal-fired power units. However, due to their inherent characteristics, coal-fired units face challenges such as degraded stability of thermal control systems when operating over a wide load range. Traditional control strategies struggle to adapt to complex operating conditions, necessitating a novel control paradigm. This paper proposes a digital twin–driven self-evolutionary optimization framework for wide-load thermal control systems of coal-fired power units. By deeply integrating digital twin technology, a high-fidelity virtual unit model is constructed to achieve real-time mapping and accurate prediction of the full life-cycle states of the physical entity. On this basis, a self-evolutionary mechanism is designed that integrates online identification and intelligent decision-making functions. The system can autonomously diagnose performance bottlenecks based on real-time data and historical experience, dynamically adjust control parameters, evaluate strategies through pre-simulation within the digital twin, and finally deploy optimized strategies to the physical system, forming a complete closed loop. This framework provides critical support for the efficient and stable wide-load operation of coal-fired power units and for the intelligent and green transformation of thermal power generation.

Keywords: Digital twin; coal-fired power unit; wide load; thermal control system; self-evolutionary optimization; intelligent control

Introduction

Energy structure transformation is an inevitable choice in addressing climate change, and China's "dual-carbon" goals are reshaping the landscape of the power system. While the large-scale grid integration of wind and solar energy increases the proportion of clean energy, it also imposes significant pressure on grid stability. Consequently, the role of coal-fired power units is shifting from "base-load power sources" to "regulating" and "supportive" power sources, requiring the capability of wide-load operation. However, coal-fired power units were originally designed for high-efficiency operation under rated conditions. When operating away from the design point—especially under low-load conditions—components such as boilers and turbines exhibit various deficiencies. The performance of conventional control loops degrades, threatening operational safety and reducing economic efficiency [1]. Previous studies have mainly focused on improving controller algorithms and optimizing operating modes, yet these approaches are constrained by "static" and "passive" limitations, with insufficient generalization and adaptability. The emergence of digital twin technology offers a new pathway to address these challenges. By enabling deep integration between the physical and information worlds, digital twins provide powerful capabilities for real-time perception, prediction, and optimization. Applying this technology to the thermal control systems of coal-fired power units makes it possible to construct a "self-evolutionary" control system. This paper proposes and elaborates on such an innovative paradigm, establishing a theoretical framework and technical system to provide forward-looking guidance for the intelligent upgrading of coal-fired power generation.

1. Theoretical Foundations and Conceptual Framework

1.1 Core Challenges of Wide-Load Thermal Control Systems

The fundamental challenges posed to thermal control systems by the wide-load operation of coal-fired power units stem from the inherent nonlinearity and time-varying nature of their physical characteristics. Under high-load conditions, subsystems operate close to their design points, where dynamic behaviors are relatively stable and linearized models remain applicable. However, as the load decreases, the dynamic characteristics of multiple subsystems undergo qualitative changes:

(1) Combustion system: The optimal values of parameters such as primary/secondary air ratio, pulverized coal concentration, and furnace thermal load vary nonlinearly with load. Under low-load conditions, the flame stability window narrows significantly, and even minor disturbances can lead to combustion deterioration.

(2) Steam–water system: The complex loops composed of feedwater pumps, high-pressure heaters, deaerators, and boiler economizers, evaporators, and superheaters exhibit substantial variations in the transfer function matrices relating flow rate, pressure, and enthalpy across different load levels. For instance, the response speed of main steam pressure to coal feed rate is markedly slower under low-load conditions.

(3) Turbine system: In sliding-pressure operation modes, the main steam pressure is no longer a constant but becomes a function of load, which complicates the originally decoupled boiler–turbine coordinated control.

Collectively, these challenges point to a central issue: the effectiveness of control strategies is highly dependent on the availability of accurate system models that are well matched to the current operating conditions. In traditional control engineering, once a model is identified and tuned, it remains unchanged for long periods. This static nature constitutes the root cause of control performance degradation under wide-load operation scenarios.

1.2 Digital Twins: An Ideal Enabler for Self-Evolution

Digital twin technology provides an ideal solution to the aforementioned model mismatch problem. A digital twin designed for the optimization of thermal control systems in coal-fired power units should possess the following core characteristics:

First, high fidelity: by integrating mechanism-based models (e.g., mass, energy, and momentum conservation equations), data-driven models (such as deep-learning-based surrogate models), and expert knowledge, the digital twin can accurately reproduce the dynamic responses of physical units under arbitrary loads and disturbances. Second, real-time capability: through an Industrial Internet of Things (IIoT) platform, the digital twin maintains millisecond-level data synchronization with the physical unit, ensuring that the virtual model state is always consistent with the physical entity [2]. Third, predictive capability: beyond reflecting the current state, the digital twin can perform high-precision predictions of system behavior over a future time horizon based on current states and control inputs. Fourth, interactivity: the digital twin supports what-if analysis, enabling virtual testing and evaluation of different control strategies and operating parameters without compromising the safety of the physical unit.

1.3 Conceptual Connotation of Self-Evolutionary Optimization

"Self-evolutionary optimization" is the core concept proposed in this paper, extending beyond traditional adaptive control. Adaptive control typically refers to the online adjustment of controller parameters according to certain performance indices, while the adaptation logic itself is predefined and fixed. In contrast, "self-evolution" implies that the very "genetic makeup" of the control system—including its control architecture, core algorithms, decision-making logic, and even objective functions—possesses the capability to continuously learn, iterate, and optimize during operation. In a self-evolutionary thermal control system, the digital twin serves as both a "brain" and an "experimental field." It continuously monitors the operational performance of the physical system and identifies performance bottlenecks. Leveraging its powerful computational and reasoning capabilities, it then explores potential optimization pathways. After ensuring the safety and effectiveness of new strategies through virtual validation, these strategies are deployed to the physical system. This process repeats iteratively, forming an ever-accelerating optimization flywheel that never ceases to evolve.

2. Digital Twin–Driven Self-Evolutionary Optimization Framework

The self-evolutionary optimization framework proposed in this paper consists of four core modules: a high-fidelity digital twin, an online state and performance perception layer, an intelligent strategy evolution engine, and a closed-loop collaborative execution layer.

2.1 Construction of a High-Fidelity Digital Twin

The digital twin is the cornerstone of the entire framework. Its construction should follow the principle of "multi-source integration and hierarchical modeling."

(1) Bottom-layer mechanism models: Based on fundamental laws such as thermodynamics, fluid mechanics, and combustion science, detailed physical models covering boilers, steam turbines, generators, and major auxiliary equipment are established. This part of the model ensures the authenticity of the twin at the level of physical laws.

(2) Middle-layer data-driven models: By leveraging historical operational big data, deep neural networks (DNNs), long short-term memory networks (LSTMs), and other models are trained to capture complex nonlinear relationships that are difficult to describe accurately using mechanism-based models (e.g., the impact of coal quality variations on combustion efficiency). These data-driven models serve as supplements to and correctors of the mechanism models [3].

(3) Top-layer knowledge graph: Unstructured knowledge such as power plant operating procedures, accident cases, and expert operational experience is transformed into a structured knowledge graph. This graph provides the digital twin with domain knowledge and constraint conditions required for decision-making.

Through data assimilation techniques, real-time sensor data from the physical unit (temperature, pressure, flow rate, valve opening, etc.) are continuously injected into the digital twin to dynamically correct internal model states, ensuring a high degree of consistency with the physical entity.

2.2 Online State and Performance Perception Layer

This layer is responsible for comprehensive, multi-dimensional monitoring and evaluation of the operating states of the physical system and the digital twin.

(1) State perception: It focuses not only on whether key process variables (PVs) are close to their setpoints (SPs), but also on in-depth analysis of the system's intrinsic health status, such as equipment wear levels, control loop stability margins, and potential unstable modes.

(2) Performance evaluation: A comprehensive key performance indicator (KPI) system is established to quantify the performance of the thermal control system. This system should include: stability indicators, such as the standard deviation of critical parameters and oscillation frequencies; accuracy indicators, such as control deviations of main steam pressure and temperature; responsiveness indicators, such as response time and overshoot following load command changes; economic indicators, such as specific coal consumption per unit of electricity generated and auxiliary power ratio; and safety indicators, such as whether key equipment parameters (e.g., drum water level and furnace negative pressure) are approaching alarm or trip thresholds.

By comparing the output differences between the physical system and the digital twin under identical inputs, regions of model mismatch can be accurately identified, providing clear direction for subsequent strategy evolution.

2.3 Intelligent Strategy Evolution Engine

This module embodies the core “intelligence” of the self-evolutionary framework and is responsible for generating and optimizing new control strategies.

(1) Problem definition: Based on the diagnostic results from the performance perception layer, optimization problems are formally defined. For example, “minimize the control deviation of main steam temperature while ensuring the safety of drum water level.”

(2) Strategy generation: The engine can employ multiple intelligent optimization methods. Reinforcement learning (RL) is a particularly promising option. Within the virtual environment constructed by the digital twin, an RL agent learns a policy that maps current states to optimal control actions through interaction with the environment via trial and error. In addition, a model predictive control (MPC) framework can also be adopted, leveraging the predictive capability of the digital twin to solve a rolling-horizon optimization problem online.

(3) Virtual validation and evaluation: All newly generated candidate strategies must first undergo rigorous, multi-scenario virtual testing within the digital twin. Test scenarios should cover normal operating conditions, typical disturbance conditions (such as sudden coal quality changes and grid frequency fluctuations), as well as extreme boundary conditions. Only strategies that pass all safety and performance evaluations are allowed to proceed to the next stage.

2.4 Closed-Loop Collaborative Execution Layer

This layer is responsible for safely and smoothly deploying the validated optimization strategies to the physical control system and forming a closed feedback loop.

(1) Strategy deployment: Through secure and reliable communication protocols, the parameters or logic of new strategies are updated to the corresponding controller modules in the distributed control system (DCS). The deployment process should be designed with smooth transition mechanisms to avoid system disturbances caused by strategy switching.

(2) Effect tracking: After deployment, the performance perception layer continuously monitors the actual performance of the strategy in the physical system and compares it with the expected outcomes predicted by the digital twin.

(3) Feedback learning: The actual operational results are fed back to the strategy evolution engine as new learning samples. If discrepancies exist between actual and expected performance, a new round of model correction and strategy optimization is triggered. In this way, a complete self-evolutionary loop of “perception–cognition–decision–execution–feedback” is achieved.

3. Key Technologies and Mechanism Design

3.1 Multi-Scale and Multi-Physical-Field Coupled Modeling Mechanism

Coal-fired power units are typical multi-scale, multi-physical-field coupled systems. The successful construction of a digital twin relies on effective coupled modeling mechanisms. For example, the combustion process involves chemical reaction kinetics (microscale), fluid flow (mesoscale), and overall furnace thermal balance (macroscale). It is therefore necessary to design cross-scale data interfaces and information transfer rules to ensure coordination and consistency among models at different scales.

3.2 Meta-Learning–Based Rapid Strategy Transfer Mechanism

The operating conditions of coal-fired power units vary significantly. If a new control strategy must be learned from scratch each time a new operating condition is encountered, efficiency would be extremely low. To address this issue, meta-learning can be introduced. The strategy evolution engine first learns a large number of control tasks under different operating conditions within the digital twin, thereby acquiring a general meta-strategy that represents “learning how to learn control” [4]. When facing a new but similar operating condition, this meta-strategy can rapidly fine-tune a high-performance strategy using only a small amount of new data, greatly enhancing the efficiency and practicality of self-evolution.

3.3 Optimization Mechanism with Embedded Safety Constraints

In the field of power generation, safety is always the top priority. Therefore, during the strategy evolution process, various hard safety constraints (such as equipment limits and operating regulations) must be embedded into the optimization algorithms. For instance, in the design of reinforcement learning reward functions, any behavior that may lead to limit violations is assigned a severe penalty; in MPC optimization problems, safety constraints are directly incorporated as hard constraints. This form of “intrinsic safety” mechanism ensures that the self-evolutionary process always operates within safe boundaries.

3.4 Human–Machine Collaborative Hybrid Intelligent Decision-Making Mechanism

Although the goal is to achieve a high level of automation, the experience and intuition of human experts remain indispensable in complex decision-making. The framework should be designed with human–machine collaboration interfaces that allow operators to review, intervene in, or provide additional heuristic information regarding the diagnostic conclusions and recommended strategies generated by the digital twin. This hybrid intelligence paradigm leverages the computational strengths of machines while integrating human domain expertise, making the self-evolutionary process more robust and trustworthy.

Conclusion

This paper systematically proposes and elaborates on the innovative theoretical framework of “digital twin–driven self-evolutionary optimization of wide-load thermal control systems for coal-fired power units.” Centered on a high-fidelity digital twin, the framework establishes a complete self-optimization ecosystem that integrates real-time perception, intelligent diagnosis, strategy evolution, virtual validation, and closed-loop execution. It fundamentally addresses the core challenges faced by traditional thermal control systems under wide-load operation, such as model mismatch and poor adaptability, and provides a novel and forward-looking solution for deep peak regulation as well as safe and economical operation of coal-fired power units. By endowing thermal control systems with the capability of “self-evolution,” this approach goes beyond optimizing a single technical system and instead reshapes the future form of traditional energy infrastructure. On the path toward achieving the “dual-carbon” goals, this paradigm—deeply integrating digital technologies with energy technologies—will undoubtedly inject strong endogenous momentum into the green, intelligent, and efficient transformation of conventional coal-fired power generation.

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