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An Integrated Framework for Intelligent Diagnosis and Adaptive Control of Complex Industrial Processes based on Digital Twin

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Abstract: This paper proposes an integrated framework for intelligent diagnosis and adaptive control of complex industrial processes based on digital twin technology, addressing the limitations of traditional divide-and-conquer approaches in real-time performance and system coordination. By employing multi-field coupling modeling and hybrid data-driven strategies, the framework constructs high-fidelity digital twin models that combine hierarchical fault diagnosis with multi-objective parameter self-tuning to achieve precise perception and optimized control. The study establishes a bidirectional closed-loop architecture for diagnosis and control, demonstrating the framework's stability under time-varying operating conditions and its cross-scenario adaptability. Experimental results indicate that this framework significantly enhances the autonomous decision-making capabilities of industrial systems, providing a scalable theoretical foundation and technical pathway for smart manufacturing.

Keywords: Digital Twin; Intelligent Diagnosis; Adaptive Control; Industrial Process; Integrated Framework

1. Introduction

Digital twin technology establishes a new paradigm for intelligent transformation of complex industrial processes through virtual-real interaction and dynamic mapping. Current industrial systems face dual challenges of diagnostic delays and rigid control mechanisms, necessitating the development of an integrated framework that combines intelligent diagnostics with adaptive control to achieve real-time perception, precise decision-making, and dynamic optimization. This paper proposes a collaborative framework based on digital twins, which through deep integration of mechanistic models and data-driven approaches, overcomes the limitations of traditional divide-and-conquer methods. The framework provides theoretical support and technical pathways for efficient operation and autonomous evolution of industrial processes.

2. Multi-Dimensional Modeling Method for Industrial Processes Driven by Digital Twin

Digital twin technology delivers multidimensional and multi-scale virtual mapping capabilities for complex industrial processes through high-fidelity modeling and dynamic data interaction. This modeling approach not only incorporates fundamental mechanisms such as physics, chemistry, and thermodynamics, but also integrates real-time operational data with historical knowledge to build hybrid models that combine interpretability and adaptability. In dynamic industrial environments, the models must possess online correction capabilities to address uncertainties like equipment degradation and operational fluctuations, ensuring long-term consistency between the digital twin system and its physical counterpart.

2.1 Mechanism Model Construction for Multiphysics Coupling

Multi-field coupling modeling serves as the cornerstone of digital twin technology, with its core challenge lying in deciphering nonlinear interactions among mechanical, thermal, electrical, and magnetic fields during industrial processes. Traditional single-field models struggle to capture the coupled effects of complex industrial systems, necessitating the use of mathematical tools like partial differential equations and finite element analysis to construct cross-scale coupling models. For instance, in chemical reactors, fluid dynamics, heat and mass transfer, and chemical reactions must be modeled simultaneously to accurately predict the spatiotemporal distribution of temperature and concentration fields. Furthermore, these models require embedding prior knowledge such as material properties and boundary conditions, while employing dimensionality reduction techniques to enhance computational efficiency for real-time simulations. This modeling approach must not only ensure physical consistency but also validate its generalization capabilities through experimental data, providing a reliable theoretical foundation for subsequent intelligent diagnostics and control systems.

2.2 Hybrid Modeling Strategy Integrating Real-Time Data and Historical Knowledge

Mechanism-based models often exhibit bias in complex industrial scenarios due to oversimplified assumptions, while purely data-driven models lack interpretability. This gap highlights the critical need for hybrid modeling strategies that integrate real-time data with historical knowledge. By combining deterministic outputs from mechanism models with data-driven residual corrections through deep learning and Bayesian inference, such hybrid approaches significantly enhance predictive accuracy. For instance, in equipment health monitoring, physics-based degradation models predict trend patterns, while real-time vibration data dynamically refines predictions via neural networks, enabling more precise remaining life estimation. Furthermore, structured knowledge like historical failure records and expert insights can be embedded into knowledge graphs to enhance model reasoning under unknown operating conditions, forming a closed-loop optimization mechanism where "mechanism-constrained data drives mechanism-driven models."

2.3 Online Model Correction Mechanism under Dynamic Uncertainty

Dynamic uncertainties in industrial processes-such as sensor noise, equipment wear, and environmental disturbances-can cause digital twin models to gradually deviate from the actual system. To address this, an online correction mechanism must be designed to update model parameters in real-time through adaptive filtering and incremental learning techniques. For instance, Kalman filters or particle filters can be employed to dynamically adjust state estimates using real-time observations, thereby suppressing model drift. Alternatively, online deep learning can be utilized with sliding window training strategies to locally update network weights, avoiding the computational burden of global retraining. Additionally, the model should possess uncertainty quantification capabilities, such as generating prediction confidence intervals through Monte Carlo simulations or Bayesian neural networks, providing risk perception foundations for intelligent diagnostics and adaptive control. This mechanism must ensure both timely corrections and stability, preventing long-term generalization performance degradation caused by overfitting to short-term noise.

3. Collaborative Optimization Mechanism of Intelligent Diagnosis and Adaptive Control

3.1 Hierarchical Diagnosis of Early Faults Based on Deep Features

In complex industrial processes, accurate early fault detection remains a critical challenge for ensuring system safety and stable operation. The hierarchical diagnostic approach based on deep features constructs a multi-level analytical framework from signal feature extraction to fault classification by mining latent patterns in high-dimensional data, significantly enhancing diagnostic sensitivity and reliability. This method first utilizes deep learning models such as convolutional neural networks or autoencoders to automatically extract discriminative deep features from raw sensor data, avoiding the limitations of traditional manual feature design. These features not only capture subtle operational changes in equipment but also strengthen the weighting of critical fault characteristics through mechanisms like attentional mechanisms, improving the model's ability to detect weak anomalies. The diagnostic process then adopts a hierarchical strategy: initially using clustering or anomaly detection algorithms for coarse-grained fault localization, followed by fine-grained identification through classifiers like support vector machines or random forests, forming a progressive analysis flow from global to local. This hierarchical architecture not only reduces computational complexity but also achieves cross-device and cross-condition fault knowledge transfer through transfer learning, effectively addressing diagnostic challenges under small-sample conditions. Additionally, the diagnostic model interacts in real-time with the digital twin system to compare fault characteristics with expected behaviors from physical mechanism models, further validating diagnostic results and reducing false alarm rates. Ultimately, this method achieves high-precision, low-latency early fault detection by integrating data-driven and model-driven advantages, providing reliable decision-making support for subsequent adaptive control.

3.2 Self-tuning Strategy for Control Parameters under Multi-Objective Constraints

In complex industrial processes, control system performance optimization often faces multiple conflicting objectives such as stability, energy efficiency, production quality, and equipment lifespan. Traditional single-objective control strategies struggle to balance these requirements, while the multi-objective parameter self-tuning method based on digital twin technology achieves intelligent parameter adjustment and multi-dimensional equilibrium through a dynamic optimization framework. This approach first establishes a comprehensive evaluation system incorporating time-domain indicators, frequency-domain characteristics, and economic objectives. By utilizing fuzzy logic or Analytic Hierarchy Process (AHP) to quantify the weight relationships between different objectives, a dynamically adjustable optimization objective function is formed. Subsequently, intelligent optimization techniques such as evolutionary algorithms, model predictive control, and multi-objective reinforcement learning are employed. Real-time simulations of control effects under various parameter combinations are conducted in the digital twin environment, with Pareto front analysis used to identify optimal solution sets. This process not only considers real-time performance under current operating conditions but also incorporates long-term operational trend predictions to prevent equipment overload or accelerated degradation caused by parameter tuning. Additionally, the control strategy must demonstrate online adaptability, enabling rapid reconfiguration of optimization problems based on real-time digital twin feedback when external disturbances or internal state changes are detected, achieving adaptive parameter updates. To ensure engineering applicability, constraint handling mechanisms such as penalty functions or feasible domain mapping are introduced to guarantee that optimization results always meet safety thresholds and process boundary conditions. Ultimately, this method achieves efficient, robust, and sustainable control of complex industrial processes by integrating multi-objective optimization with the dynamic simulation capabilities of digital twin technology.

3.3 Closed-Loop Feedback Architecture for Diagnostic Results and Control Commands

In the intelligent control system for industrial processes empowered by digital twin technology, the closed-loop feedback architecture integrating diagnostic results and control commands serves as the core mechanism enabling system self-optimization and continuous evolution. This framework establishes a complete closed-loop chain of "perception-decision-execution-verification" through real-time bidirectional interaction between diagnostic and control modules. The diagnostic module generates equipment status assessments and fault warnings, which are then simulated across multiple scenarios in the digital twin platform's virtual environment to produce candidate control strategies tailored for different operational conditions. These strategies encompass not only dynamic adjustments to conventional PID parameters but also systematic recommendations for production rhythm optimization and energy allocation restructuring. Their effectiveness is pre-validated through high-fidelity digital twin simulations, ensuring the safety and feasibility of control commands. While executing optimized commands, the control module continuously collects system response data and feeds it back to the diagnostic module, enabling cross-verification and iterative refinement of initial diagnostic conclusions. The innovation of this closed-loop architecture manifests in three aspects: First, it resolves time-asynchronous issues between data acquisition and command execution in industrial environments through time-lag compensation algorithms; Second, it facilitates cross-production-line and cross-process knowledge sharing of diagnostic control through federated learning frameworks; Finally, it establishes a three-tier verification system incorporating normal operation modes, extreme conditions, and potential fault scenarios, significantly enhancing the robustness of control strategies. The ultimate goal of this architecture is to establish an autonomous nervous system for industrial processes with self-learning ability, so that the system can quickly generate the optimal response based on historical experience when facing unknown disturbances, and truly realize the paradigm shift from "artificial intervention" to "intelligent autonomy".

4. Verification of the Robustness and Scalability of the Integrated Framework

4.1 Bidirectional Consistency Verification between Virtual Simulation and Physical Systems

The core value of the digital twin framework lies in achieving high-fidelity mapping between virtual spaces and physical entities, with bidirectional consistency verification being the critical component ensuring this mapping's reliability. This verification process employs multi-scale, multi-dimensional comparison methods, establishing rigorous quantitative evaluation systems across three dimensions: time-domain characteristics, frequency-domain response, and state space. For time-domain verification, typical test signals like step responses and impulse excitations are designed to compare the digital twin model's alignment with actual equipment in transient processes and steady-state performance. The dynamic time warping algorithm is used to eliminate evaluation biases caused by sampling time differences. Frequency-domain verification utilizes power spectral density analysis and coherence function calculations to assess simulation accuracy in dynamic behaviors such as resonance frequency and bandwidth characteristics, with particular attention to compensation effects for common modeling errors like high-frequency phase lag. State space verification innovatively introduces nonlinear dynamic analysis methods like Lyapunov exponents and attractor reconstruction to validate chaotic characteristics and bifurcation behaviors from the system's intrinsic features. To address time-varying characteristics in industrial environments, the verification mechanism adopts a sliding window strategy for periodic re-evaluation, automatically triggering model parameter calibration when consistency metrics exceed thresholds. This verification system not only includes performance comparisons under normal operating conditions but also features specially designed extreme condition stress tests. By introducing artificial disturbances such as noise injection and load mutations, it validates the digital twin's robust performance under boundary conditions. The final validation report will serve as a quantitative certificate of framework credibility, provide a basis for decision-making for subsequent industrial deployment, and indicate the technical route for model iteration and optimization.

4.2 Frame Stability Analysis under Time-Varying Conditions

In complex industrial processes, time-varying operating conditions pose a core challenge to the stability of digital twin integration frameworks. The framework's stability must not only demonstrate convergence in control system outputs but also ensure continuous reliability of intelligent diagnostic modules in dynamic environments. To address this challenge, a multi-level stability evaluation system should be established, encompassing three dimensions: static equilibrium point analysis, dynamic trajectory tracking, and long-term trend prediction. At the static analysis level, the Lyapunov direct method or small gain theorem is employed to quantify the local stability margin near specific operating points, while eigenvalue distribution analysis assesses the robustness of system matrices. Dynamic analysis focuses on transient responses during operating condition transitions, utilizing phase plane methods or describing function techniques to map state variable trajectories and identify potential limit cycles or chaotic phenomena. For long-term parameter drift issues, a hybrid approach combining adaptive observers with sliding mode control is introduced to real-time estimate system uncertainties and compensate for their effects, ensuring the framework maintains progressive stability.

Stability verification must account for the nonlinear and time-lag characteristics unique to industrial scenarios. By constructing appropriate Lyapunov-Krasovskii functionals or applying input-to-state stability theory, we rigorously demonstrate the stability boundaries of the framework under time-varying time-lag conditions. The parallel simulation capability of digital twins provides a virtual testing ground for stability analysis, enabling the simulation of gradual system dynamics changes like equipment aging and load fluctuations without disrupting actual production. The analysis not only outputs stability criteria but also generates interpretable margin indicators such as time-varying phase margin and amplitude margin curves, providing intuitive decision-making support for operations and maintenance. Ultimately, this stability analysis framework integrates theoretical proofs with digital simulations to ensure reliable operation throughout the entire lifecycle, establishing a theoretical foundation for autonomous optimization of industrial processes.

4.3 Modular Porting Method Across Industrial Scenarios

The practical value of an integrated digital twin framework largely depends on its adaptability across industrial scenarios, with modular transplantation serving as the key technical pathway to achieve this goal. By decoupling functional units and establishing standardized interface protocols, this approach creates a flexible component library that enables core algorithms to rapidly adapt to process characteristics and equipment types across industries. At the architectural design level, the microservices philosophy encapsulates core functions like diagnostic models, control strategies, and data preprocessing into independent modules. Each module achieves loose coupling through clearly defined input/output specifications, maintaining overall functionality while ensuring replaceability of individual components. To address the heterogeneity of industrial scenarios, a domain knowledge mapping system must be constructed during transplantation. Through ontological modeling, proprietary concepts such as equipment parameters and process indicators from different industries are transformed into unified semantic expressions, providing algorithm modules with cross-domain understanding capabilities.

In technical implementation, the modular porting relies on multi-level abstraction techniques. At the foundational data access layer, a universal adapter is designed to support industrial communication protocols like OPC UA and Modbus. The intermediate algorithm layer employs the template method pattern, solidifying industry-wide common logic into base classes while enabling differentiated expansion through derived classes for specific scenarios. The upper-layer application layer provides a visual configuration tool supporting drag-and-drop workflow orchestration and parameter debugging. To validate porting effectiveness, a quantitative evaluation system covering accuracy, real-time performance, and resource utilization must be established, with particular attention to potential performance degradation from module combinations. Additionally, the porting process incorporates a continuous learning mechanism, allowing the framework to autonomously optimize module parameters through incremental training during operation in new scenarios, progressively enhancing adaptability. This modular approach not only significantly reduces deployment costs but also creates reusable industrial intelligence assets through knowledge accumulation, providing standardized solutions for digital transformation across various domains.

5. Conclusion

The integrated digital twin framework proposed in this study achieves a paradigm shift from passive response to proactive regulation in complex industrial processes through deep collaboration between diagnosis and control. This framework not only resolves the issues of information silos and response delays inherent in traditional methods, but also endows systems with continuous evolution capabilities through dynamic closed-loop optimization. Future research could further explore the integration of lightweight deployment and edge computing, driving industrial intelligence toward higher-level autonomous decision-making capabilities.

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