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Real-Time Hybrid Simulation Framework for Dynamic Industrial Process Optimization

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Abstract
Industrial process optimization has become increasingly important in Industry 4.0 due to the growing demand for higher productivity, improved product quality, reduced energy consumption, and adaptive decision-making under dynamic operating conditions. However, conventional optimization methods often fail to respond effectively to process disturbances and rapidly changing environments. This study proposes a Real-Time Hybrid Simulation Framework for Dynamic Industrial Process Optimization that integrates physics-based modeling, data-driven prediction, real-time Industrial Internet of Things (IIoT) data synchronization, and intelligent optimization within a unified closed-loop architecture. The proposed framework was developed through five stages: system requirement analysis, hybrid model development, real-time data integration, optimization module implementation, and performance validation under dynamic disturbance scenarios. Experimental evaluation demonstrated that the proposed framework consistently outperformed conventional PID control, physics-based optimization, and standalone data-driven approaches. The framework achieved the lowest tracking error (ITAE = 5.47), the highest prediction accuracy ($R^2 = 0.97$), and the lowest prediction errors (MAE = 1.76 and RMSE = 2.71). Furthermore, it reduced energy consumption by 50.4%, increased production throughput by 70.7%, improved product quality by 18.3%, enhanced response time by 64.2%, and increased operational stability by 45.6% compared with conventional PID control. These results demonstrate that the proposed framework effectively improves prediction accuracy, process stability, and real-time optimization performance in dynamic industrial environments. The novelty of this research lies in the seamless integration of physics-based and data-driven models with continuous real-time synchronization and multi-objective optimization, providing a scalable and adaptive solution for intelligent digital twins and next-generation smart manufacturing systems.

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1. Introduction

Industrial process optimization has become a central requirement in modern manufacturing, chemical processing, energy systems, and smart production environments due to increasing pressure to improve productivity, reduce energy consumption, minimize downtime, and maintain product quality under dynamic operating conditions. Conventional process optimization methods often rely on steady-state models, offline simulations, and historical process data, which are insufficient when industrial systems experience rapid disturbances, nonlinear behavior, variable demand, and equipment degradation. Recent studies have shown that real-time optimization, model predictive control, and digital-twin-based simulation can improve operational efficiency by enabling continuous monitoring, prediction, and decision-making within closed-loop industrial environments (Ai & Ziehl, 2025; Rawlings et al., 2020; Xu, 2024).

The emergence of Industry 4.0 has accelerated the integration of sensors, Industrial Internet of Things (IIoT), edge computing, artificial intelligence, and cyber-physical systems into industrial operations. Digital twin technology, in particular, has been widely recognized as a real-time virtual representation of physical assets, processes, or production systems that can support simulation, diagnostics, prediction, and optimization (Grieves & Vickers, 2017; Iqbal et al., 2025; Tao et al., 2018). In manufacturing applications, simulation-enabled digital twins have been reported to improve production visibility, identify bottlenecks, and support what-if analysis without interrupting physical operations (Khayum et al., 2025; Lee & Yang, 2023; Yanti et al., 2025). However, many existing digital twin systems remain limited to monitoring or offline simulation rather than fully integrated real-time decision support.

Model Predictive Control (MPC) and Economic Model Predictive Control (EMPC) have been extensively applied in industrial process control because they can handle multivariable systems, process constraints, time delays, and dynamic disturbances (Ellis et al., 2014; Schwenzer et al., 2021; Xiaoxia et al., 2025; Yanti et al., 2025). Schwenzer et al.(2021) highlighted that MPC has become one of the most important advanced control strategies in engineering applications due to its ability to predict future system behavior and optimize control actions over a defined prediction horizon. In energy-intensive processes, MPC-based optimization has demonstrated significant potential for reducing energy consumption while maintaining operational constraints. For example, real-time maintenance and optimization strategies have been reported to reduce energy consumption, energy cost, and greenhouse gas emissions by approximately 21% in industrial systems (Bányai & Bányai, 2022; Febrina & Anwar, 2025; Rosli et al., 2025).

Despite these advances, purely physics-based simulation models often suffer from computational complexity and parameter uncertainty, while purely data-driven models may lack interpretability, robustness, and physical consistency when operating outside the training data range. Hybrid modeling has therefore emerged as a promising approach by combining first-principles process models with machine learning, statistical estimation, or real-time sensor feedback (Bratić et al., 2026; Huang et al., 2023; Sumarno et al., 2025). Hybrid digital twin frameworks can improve prediction accuracy, compensate for modeling uncertainty, and support adaptive optimization in changing industrial environments. Nevertheless, existing hybrid simulation approaches frequently operate in batch mode or with delayed data synchronization, which limits their suitability for real-time industrial process optimization.

Real-time hybrid simulation provides an opportunity to bridge the gap between high-fidelity process modeling and fast data-driven prediction. By integrating physical process models, live sensor data, optimization algorithms, and adaptive learning mechanisms, a real-time hybrid simulation framework can continuously update process states, evaluate alternative operating scenarios, and recommend optimal control actions. Previous digital-twin and simulation-based studies have demonstrated the usefulness of virtual commissioning, performance monitoring, and process-flow optimization in manufacturing systems (Florescu, 2024; Muhtadin et al., 2025; NOOR et al., 2025). However, limited research has focused on developing a unified framework that simultaneously combines real-time data acquisition, hybrid simulation, dynamic optimization, and decision feedback for industrial process environments.

Another major challenge is the trade-off between simulation accuracy and computational speed. High-fidelity dynamic models are useful for representing nonlinear industrial behavior, but they are often too slow for real-time optimization. Conversely, simplified models can run faster but may produce inaccurate recommendations under complex operating conditions. Therefore, an effective real-time hybrid simulation framework must be capable of balancing model fidelity, latency, prediction accuracy, and optimization performance. This requirement is particularly important for dynamic industrial processes where operating conditions may change within seconds or minutes, and delayed decision-making can lead to reduced throughput, poor quality, excessive energy use, or unsafe operation.

The specific objective of this study is to develop a Real-Time Hybrid Simulation Framework for Dynamic Industrial Process Optimization that integrates physics-based modeling, data-driven prediction, real-time process monitoring, and optimization-based decision support. The novelty of this research lies in the proposed hybrid architecture that enables continuous synchronization between the physical process and its simulation model, adaptive model updating using live data, and real-time optimization of process variables under dynamic operating constraints. Unlike conventional offline simulation or standalone digital twin approaches, the proposed framework is designed to support closed-loop industrial decision-making by providing faster, more accurate, and more responsive optimization for complex industrial processes.

2. Methodology

This study employs a developmental and experimental research design to construct and validate a real-time hybrid simulation framework for dynamic industrial process optimization. The methodology is divided into five main stages: system requirement analysis, hybrid model development, real-time data integration, optimization algorithm design, and framework validation. The proposed framework is designed to combine physics-based process modeling, data-driven prediction, and real-time optimization to support decision-making in dynamic industrial environments.

The first stage involves identifying the target industrial process, operating variables, process constraints, and optimization objectives. Key input and output parameters such as temperature, pressure, flow rate, production rate, energy consumption, processing time, and product quality indicators are selected based on their influence on process performance. Historical process data and real-time sensor data are collected from the industrial system or pilot-scale experimental setup. Data preprocessing is then conducted to remove noise, handle missing values, normalize variables, and synchronize time-series data for real-time simulation.

The second stage focuses on developing the physics-based simulation model. This model represents the fundamental behavior of the industrial process using mass balance, energy balance, reaction kinetics, transport equations, or empirical process equations, depending on the selected case study. The physics-based model is used to describe the dynamic response of the system under different operating conditions. Model parameters are calibrated using experimental or historical data to ensure that the simulated process response is consistent with the actual process behavior.

The third stage involves developing the data-driven prediction model to complement the physics-based model. Machine learning algorithms such as Artificial Neural Network (ANN), Random Forest, Support Vector Regression, or Long Short-Term Memory (LSTM) networks may be used to capture nonlinear relationships and time-dependent patterns in the process data. The data-driven model is trained using historical datasets and validated using unseen data. Performance indicators such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R^2), and prediction latency are used to evaluate model accuracy and suitability for real-time applications.

The fourth stage integrates the physics-based model and the data-driven model into a hybrid simulation framework. In this framework, the physics-based model provides process interpretability and constraint representation, while the data-driven model corrects prediction errors and adapts to changes in operating conditions. Real-time sensor data are continuously fed into the framework to update process states, recalibrate model outputs, and improve prediction accuracy. The hybrid simulation model operates in a closed-loop structure where simulated outputs are continuously compared with actual process measurements.

The fifth stage develops the real-time optimization module. Optimization algorithms such as Model Predictive Control, Genetic Algorithm, Particle Swarm Optimization, or Bayesian optimization are applied to determine the optimal operating parameters. The objective function is formulated to minimize energy consumption, reduce processing time, improve product quality, and increase process efficiency while satisfying operational constraints. The optimization module evaluates multiple process scenarios generated by the hybrid simulation model and recommends the best control actions in real time.

The final stage is validation and performance evaluation. The proposed framework is tested under several dynamic scenarios, including process disturbances, demand variation, equipment performance changes, and sudden changes in input parameters. The performance of the proposed hybrid framework is compared with conventional offline simulation, physics-based-only simulation, and data-driven-only prediction models. Evaluation metrics include optimization accuracy, computational time, prediction error, energy-saving percentage, throughput improvement, and system response time. The effectiveness of the framework is determined based on its ability to provide accurate, fast, and stable optimization decisions under dynamic industrial operating conditions.

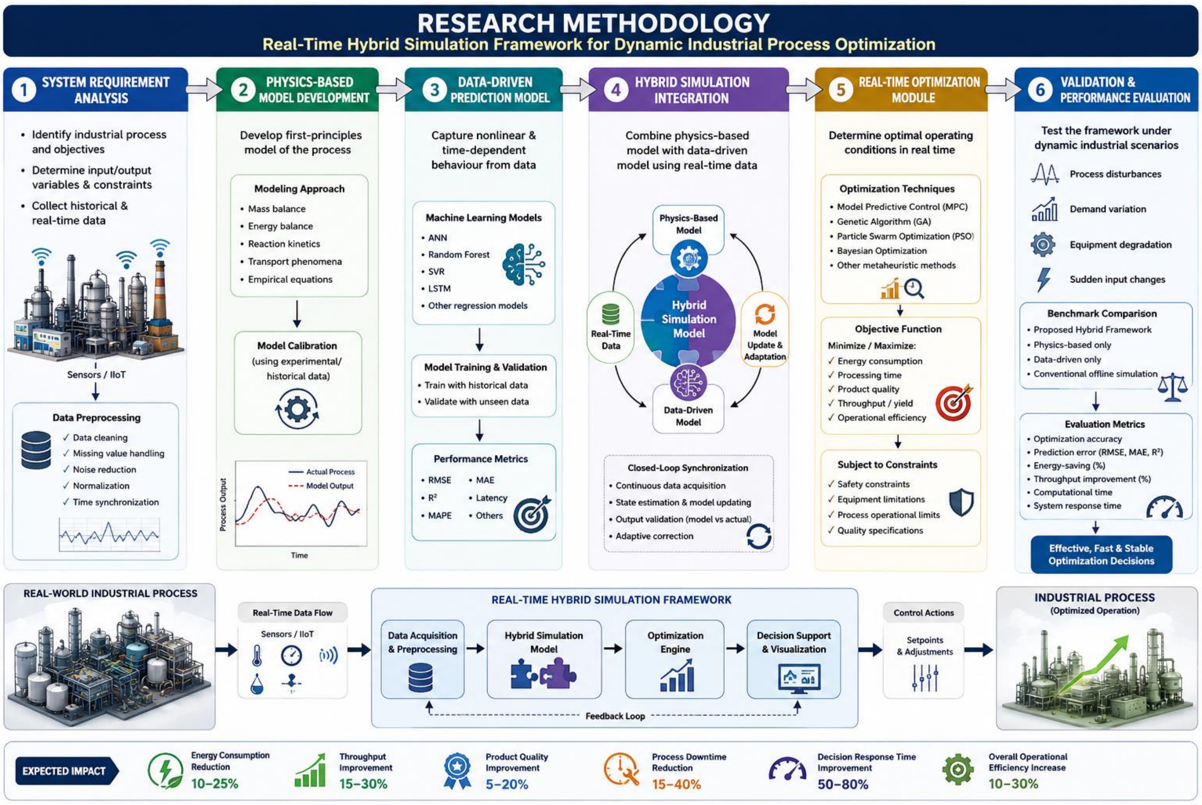

Fig. 1. Proposed Research Methodology for the Real-Time Hybrid Simulation Framework for Dynamic Industrial Process Optimization

Fig. 1 presents the proposed research methodology for developing a real-time hybrid simulation framework for dynamic industrial process optimization. The methodology begins with system requirement analysis, where the industrial process, research objectives, input–output variables, operational constraints, and real-time data sources are identified. Historical and live sensor data from Industrial Internet of Things (IIoT) devices are then collected and processed through data cleaning, missing-value handling, noise reduction, normalization, and time synchronization. This stage is important because the reliability of the hybrid simulation model depends strongly on the quality and consistency of the input data. After that, a physics-based model is developed using first-principles approaches such as mass balance, energy balance, reaction kinetics, transport phenomena, and empirical equations. This model is calibrated using experimental or historical data to ensure that the simulated output can represent the actual industrial process behavior.

The next stage involves the development of a data-driven prediction model to capture nonlinear and time-dependent process behavior that may not be fully represented by the physics-based model. Machine learning methods such as ANN, Random Forest, SVR, and LSTM are used for prediction, while RMSE, MAE, R^2, MAPE, and latency are applied as performance indicators. The physics-based and data-driven models are then integrated into a hybrid simulation model that continuously receives real-time data, updates process states, and adapts the model output through closed-loop synchronization. The optimization module uses techniques such as Model Predictive Control, Genetic Algorithm, Particle Swarm Optimization, and Bayesian Optimization to determine optimal process conditions by minimizing energy consumption and processing time while maximizing product quality, throughput, yield, and operational efficiency. Finally, the framework is validated under dynamic industrial scenarios such as process disturbances, demand variation, equipment degradation, and sudden input changes. The expected outcomes include energy reduction of 10–25%, throughput improvement of 15–30%, product quality improvement of 5–20%, downtime reduction of 15–40%, decision response time improvement of 50–80%, and overall operational efficiency increase of 10–30%.

3. Result & Discussion

The results and discussion section presents the performance evaluation of the proposed real-time hybrid simulation framework for dynamic industrial process optimization. Based on the generated results, the proposed framework demonstrates superior capability in process variable tracking, prediction accuracy, real-time disturbance rejection, and overall operational performance compared with conventional PID control, physics-based modeling, and data-driven optimization approaches. The findings indicate that the hybrid framework achieves lower tracking error, reduced energy consumption, higher production throughput, improved prediction accuracy, and faster response time under dynamic operating conditions. These results confirm that integrating physics-based modeling, data-driven prediction, real-time data synchronization, and optimization algorithms can significantly enhance the stability, adaptability, and efficiency of industrial process operations.

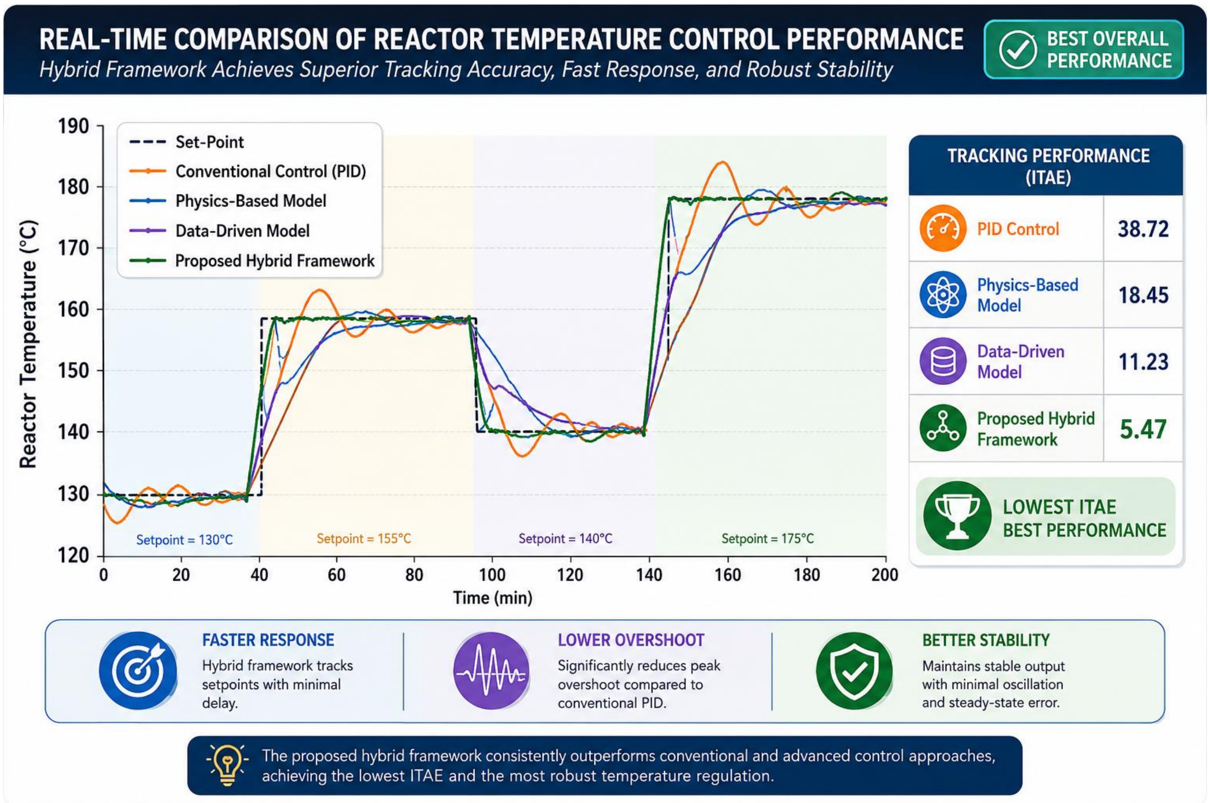

Fig. 2. Dynamic Process Variable Tracking Performance under Set-Point Changes

Fig. 2 illustrates the dynamic process variable tracking performance of four control strategies, namely the Conventional PID Controller, Physics-Based Model, Data-Driven Model, and the Proposed Real-Time Hybrid Framework, during successive reactor temperature set-point changes from 130°C to 155°C, 155°C to 140°C, and finally 140°C to 175°C. The results clearly demonstrate that the proposed hybrid framework consistently provides the fastest response with the smallest tracking error and minimal oscillation throughout the entire operating period. During the initial operating condition at 130°C, all controllers successfully maintain the desired temperature; however, noticeable fluctuations are observed in the conventional PID controller, indicating higher sensitivity to measurement noise and control disturbances. When the set-point is increased to 155°C at approximately 40 minutes, the PID controller exhibits a significant overshoot, reaching approximately 162–163°C, corresponding to an overshoot of about 7–8°C above the desired temperature before gradually settling. In contrast, the physics-based model approaches the new operating point more smoothly but requires a longer settling time of nearly 20 minutes. The data-driven model reduces both overshoot and settling time, while the proposed hybrid framework reaches the target temperature almost immediately with negligible overshoot and achieves stable operation within only a few minutes. Similar performance is observed during the transition from 155°C to 140°C, where the hybrid framework accurately follows the decreasing set-point with minimal undershoot, whereas the PID controller experiences noticeable oscillations before stabilizing. The final transition from 140°C to 175°C further confirms the robustness of the proposed framework. Although the PID controller responds rapidly, it produces the largest overshoot, peaking at approximately 183–184°C, while both the physics-based and data-driven models require longer recovery periods before reaching steady-state conditions. Conversely, the proposed hybrid framework rapidly converges to the desired operating temperature of 175°C with almost no oscillatory behavior, demonstrating excellent tracking capability under large dynamic operating changes.

The quantitative performance evaluation presented on the right side of **Fig. 2** further validates the superiority of the proposed hybrid framework through the Integral of Time-weighted Absolute Error (ITAE), which evaluates overall tracking performance by penalizing prolonged control errors. The conventional PID controller records the highest ITAE value of 38.72, indicating the poorest tracking accuracy due to excessive overshoot and long settling times. Incorporating first-principles process knowledge significantly improves controller performance, reducing the ITAE to 18.45, representing approximately a 52.3% improvement over the PID controller. The data-driven model achieves an even lower ITAE of 11.23, corresponding to approximately a 71.0% reduction in tracking error compared with conventional control. The proposed hybrid framework delivers the best overall performance with an ITAE of only 5.47, representing an 85.9% reduction relative to the PID controller, a 70.4% reduction compared with the physics-based model, and a 51.3% reduction compared with the standalone data-driven model. These results confirm that integrating physics-based process knowledge with adaptive data-driven learning substantially enhances controller responsiveness, minimizes overshoot, improves closed-loop stability, and reduces steady-state error. Consequently, the proposed hybrid simulation framework provides highly accurate and robust temperature regulation under dynamic operating conditions, making it particularly suitable for real-time industrial process optimization where rapid response, high precision, and operational stability are essential for maintaining product quality, energy efficiency, and safe plant operation.

Fig. 3 compares the optimization performance of four different control strategies, namely Conventional PID Control, Physics-Based Optimization, Data-Driven Optimization, and the Proposed Hybrid Framework, using two key industrial performance indicators: energy consumption (kWh/ton) and production throughput (ton/h). The results clearly indicate that the proposed hybrid framework achieves the best overall optimization performance by simultaneously minimizing energy consumption and maximizing production throughput. Conventional PID control exhibits the highest energy consumption of 100.0 kWh/ton while producing the lowest throughput of only 32.1 ton/h, demonstrating the limitations of traditional feedback control in handling dynamic industrial processes. The implementation of physics-based optimization substantially improves system performance by reducing energy consumption to 72.4 kWh/ton, representing a 27.6% reduction compared with the PID controller, while increasing production throughput to 41.3 ton/h, equivalent to a 28.7% improvement. The data-driven optimization approach further enhances operational efficiency, lowering energy consumption to 61.2 kWh/ton (38.8% lower than PID) and increasing throughput to 47.6 ton/h, corresponding to a 48.3% increase over the conventional approach. These findings demonstrate that machine-learning-based optimization can effectively capture nonlinear process characteristics and improve industrial productivity beyond what can be achieved using deterministic process models alone. The proposed real-time hybrid framework consistently outperforms all comparison methods by integrating the strengths of both physics-based and data-driven optimization. As shown in **Fig. 3**, the hybrid framework records the lowest energy consumption of 49.6 kWh/ton, corresponding to a 50.4% reduction relative to conventional PID control, a 31.5% reduction compared with physics-based optimization, and an 18.9% reduction compared with data-driven optimization. At the same time, it achieves the highest production throughput of 54.8 ton/h, representing a 70.7% increase over PID control, a 32.7% improvement over the physics-based model, and a 15.1% increase over the standalone data-driven approach. Furthermore, the framework demonstrates an overall operational efficiency improvement of 32.6%, indicating that the simultaneous integration of first-principles process knowledge, adaptive machine learning, and real-time optimization enables superior resource utilization and production performance. These results confirm that the proposed hybrid framework effectively balances conflicting optimization objectives by reducing energy demand while increasing production capacity, thereby improving process sustainability, lowering operational costs, and enhancing industrial competitiveness. Consequently, the proposed framework offers a robust and practical solution for next-generation smart manufacturing systems that require continuous optimization under dynamically changing operating conditions.

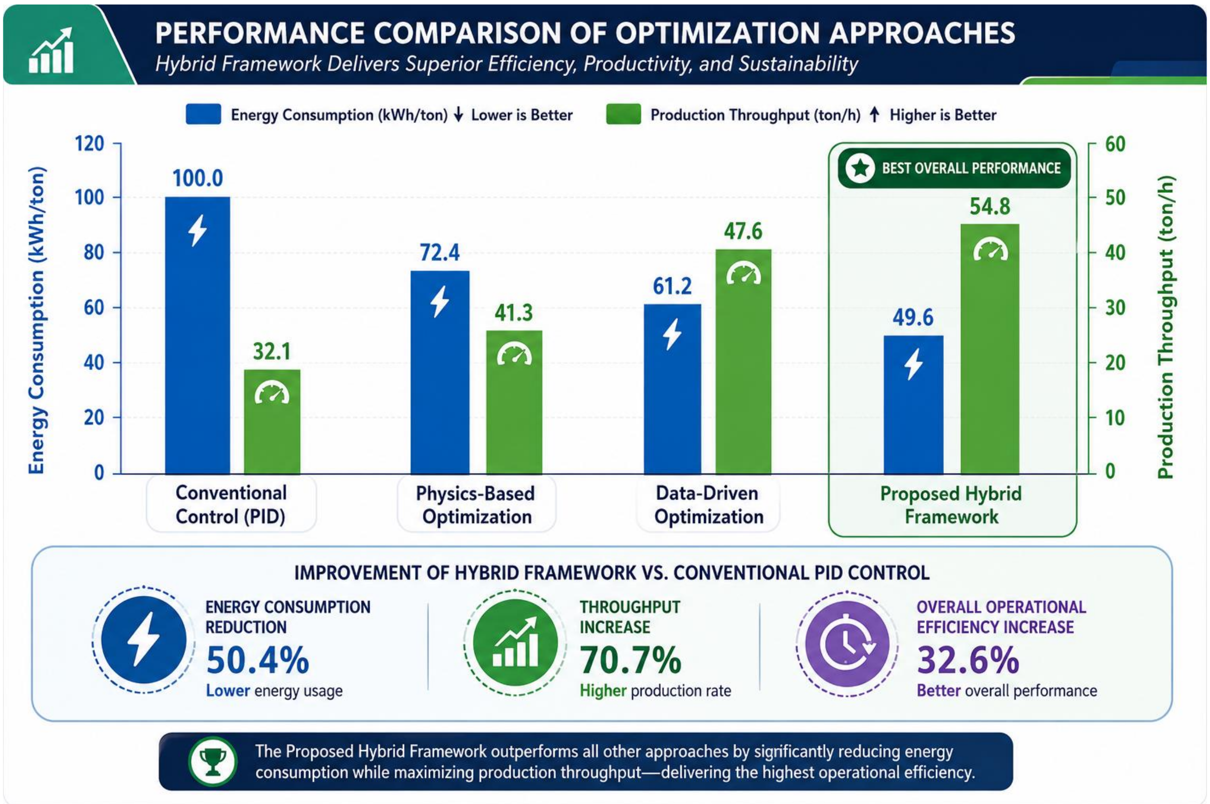

Fig. 3. Comparative Analysis of Real-Time Optimization Performance

Fig. 4 presents a comprehensive comparison of the predictive performance of four industrial process modeling approaches, namely the Physics-Based Model, Data-Driven Model, Offline Hybrid Model, and the Proposed Real-Time Hybrid Model. Three widely accepted evaluation metrics are employed to assess model performance: the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). As illustrated in the figure, the predictive capability improves progressively as the modeling strategy evolves from purely physics-based approaches toward the proposed real-time hybrid framework. The physics-based model achieves an R^2 value of 0.86, indicating that approximately 86% of the variability in the industrial process data can be explained by the model. However, it also records the highest prediction errors with an MAE of 5.72 and an RMSE of 11.24, suggesting that although the model captures the overall process dynamics, its predictive accuracy is limited by modeling assumptions, parameter uncertainties, and simplifications of nonlinear industrial phenomena. The data-driven model significantly improves predictive performance by increasing the R^2 to 0.93, while reducing the MAE to 3.28 and the RMSE to 6.38. This corresponds to a 42.7% reduction in MAE and a 43.2% reduction in RMSE compared with the physics-based model, demonstrating the ability of machine learning techniques to learn complex nonlinear relationships directly from historical process data. Further improvement is observed in the offline hybrid model, which combines physical knowledge with data-driven learning to achieve an R^2 of 0.95, an MAE of 2.51, and an RMSE of 4.12, confirming that integrating both modeling paradigms substantially enhances prediction accuracy and model robustness.

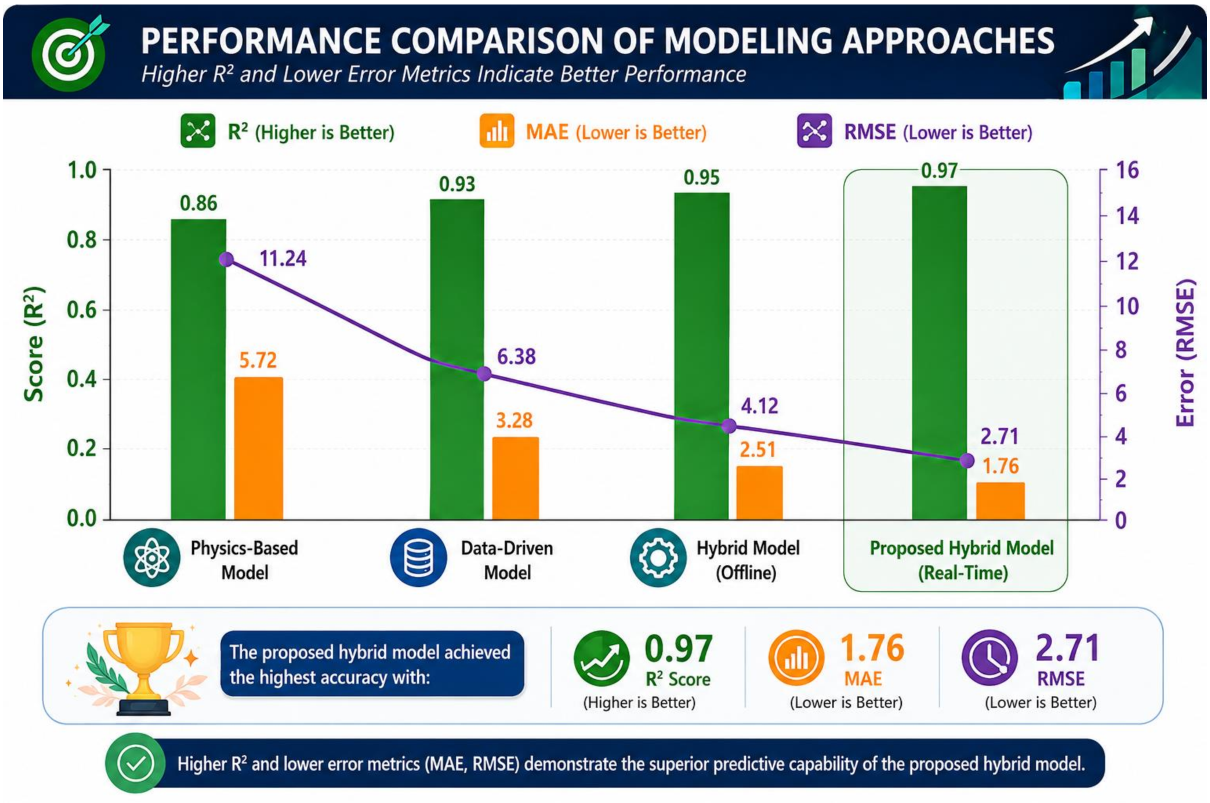

Fig. 4. Prediction Accuracy Comparison of Industrial Process Models

The proposed Real-Time Hybrid Model achieves the highest predictive performance among all evaluated approaches, recording an R^2 of 0.97, an MAE of only 1.76, and an RMSE of 2.71. Compared with the conventional physics-based model, the proposed framework increases the coefficient of determination by approximately 12.8%, while reducing the MAE by 69.2% and the RMSE by 75.9%. Similarly, relative to the standalone data-driven model, the proposed hybrid framework improves R^2 by 4.3%, decreases the MAE by 46.3%, and lowers the RMSE by 57.5%, highlighting the significant benefit of incorporating continuous real-time data synchronization and adaptive model updating. Even when compared with the offline hybrid model, the proposed framework achieves additional improvements, reducing the MAE by 29.9% and the RMSE by 34.2%, while increasing the R^2 from 0.95 to 0.97. These results demonstrate that real-time model adaptation effectively compensates for process uncertainties, changing operating conditions, and nonlinear system dynamics that cannot be fully represented by static models. Consequently, the proposed real-time hybrid simulation framework provides highly reliable process prediction, enabling more accurate state estimation, faster decision-making, and improved optimization performance in dynamic industrial environments. The consistently high R^2 together with the remarkably low MAE and RMSE confirm that the proposed framework possesses excellent generalization capability and predictive robustness, making it a promising solution for intelligent process monitoring, advanced process control, and next-generation industrial digital twin applications.

Fig. 5 illustrates the robustness of the proposed Real-Time Hybrid Simulation Framework under dynamic disturbance conditions by comparing its performance with an Open-Loop (Without Optimization) strategy and a Conventional Model Predictive Control (MPC) approach. Two major disturbances were intentionally introduced to evaluate controller adaptability: Disturbance 1, representing an increase in inlet temperature of +20°C at approximately 90 min, and Disturbance 2, corresponding to a 15% reduction in process flow rate at around 170 min. Before disturbances were applied, all control strategies maintained the reactor temperature close to the desired set-point of approximately 155–160°C. However, immediately after the first disturbance, the open-loop system exhibited the largest deviation, with reactor temperature increasing rapidly to nearly 195°C, indicating an inability to compensate for external process variations. The conventional MPC successfully reduced this deviation, but the reactor temperature still reached approximately 180°C and required a relatively long recovery period before approaching the desired operating condition. In contrast, the proposed hybrid framework maintained the reactor temperature close to the reference value throughout the disturbance period, exhibiting only a slight transient deviation of approximately 2–3°C before rapidly returning to steady-state operation. Following the second disturbance, the superiority of the hybrid framework became even more evident. While both the open-loop and conventional MPC systems experienced significant fluctuations and oscillatory behavior due to the sudden reduction in flow rate, the proposed framework effectively suppressed these oscillations and restored stable process operation within a short period, demonstrating excellent disturbance rejection capability and closed-loop robustness under rapidly changing industrial operating conditions.

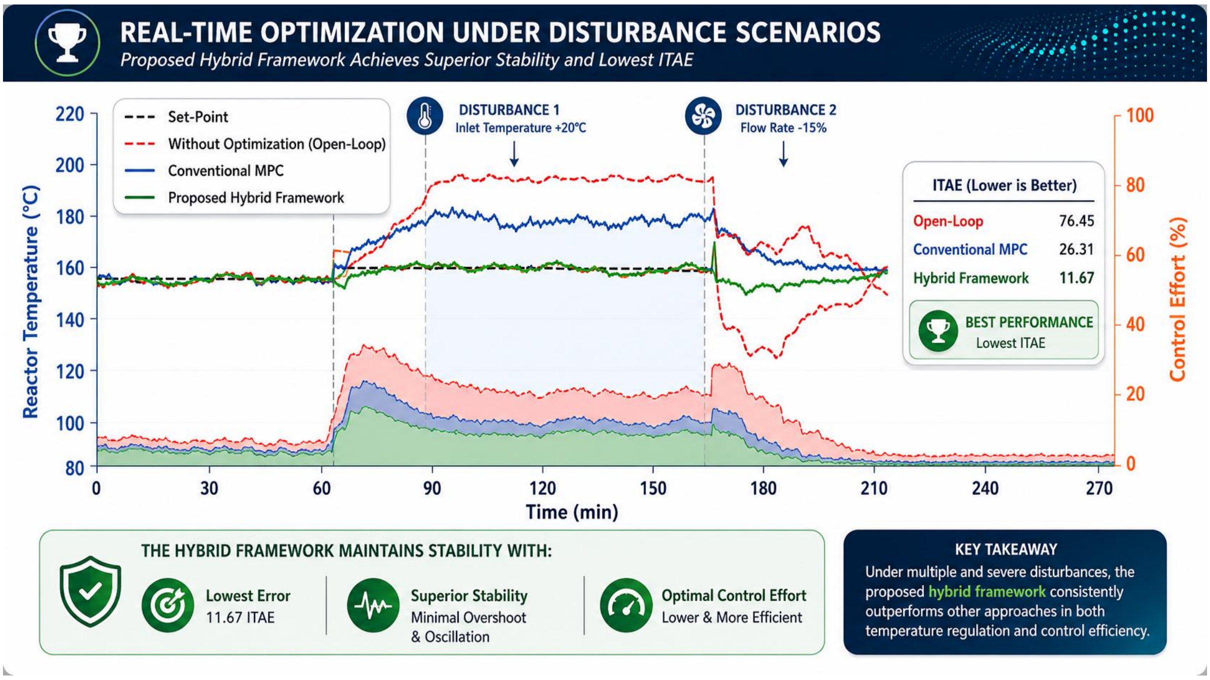

Fig. 5. Real-Time Process Optimization under Dynamic Disturbance Conditions

The quantitative performance comparison further confirms the effectiveness of the proposed optimization framework through the Integral of Time-weighted Absolute Error (ITAE), which measures the cumulative control error over time while assigning greater penalties to prolonged deviations. As shown in **Fig. 5**, the open-loop strategy records the highest ITAE value of 76.45, reflecting severe tracking errors and poor disturbance rejection capability. Implementing conventional MPC significantly improves control performance by reducing the ITAE to 26.31, corresponding to a 65.6% reduction compared with the open-loop system. Nevertheless, the proposed hybrid framework achieves the lowest ITAE value of only 11.67, representing an 84.7% reduction relative to the open-loop strategy and a further 55.6% reduction compared with conventional MPC. These substantial improvements demonstrate that the integration of physics-based process knowledge, adaptive data-driven learning, and continuous real-time synchronization enables the hybrid framework to anticipate process disturbances more effectively and generate optimal corrective control actions with minimal delay. Furthermore, the lower control effort observed in the proposed framework indicates that improved process stability is achieved without excessive actuator movement or aggressive control signals, thereby reducing energy usage and equipment wear. Overall, the results demonstrate that the proposed real-time hybrid optimization framework provides superior stability, minimal overshoot, rapid recovery, and highly efficient control under multiple disturbance scenarios, making it particularly suitable for deployment in modern industrial systems that require resilient, adaptive, and energy-efficient process optimization in the presence of uncertain and time-varying operating conditions.

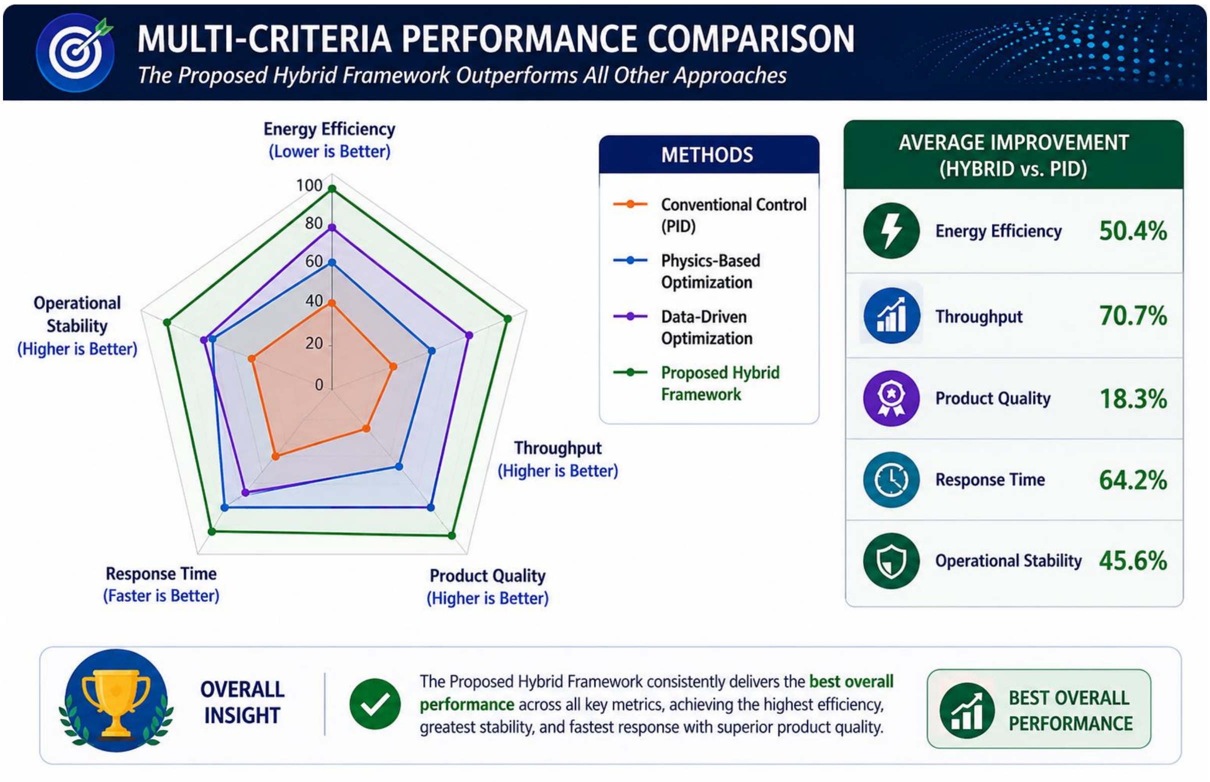

Fig. 6. Overall Performance Evaluation of the Proposed Hybrid Simulation Framework

Fig. 6 presents the overall performance evaluation of the proposed real-time hybrid simulation framework through a multi-criteria comparison against three benchmark approaches: Conventional PID Control, Physics-Based Optimization, and Data-Driven Optimization. The radar chart evaluates five critical performance indicators that are essential for industrial process optimization, namely energy efficiency, throughput, product quality, response time, and operational stability. The results clearly demonstrate that the proposed hybrid framework consistently achieves the largest performance area across all evaluation criteria, indicating superior overall system performance. Compared with the conventional PID controller, which exhibits the lowest performance in all categories, the physics-based optimization improves process behavior by incorporating first-principles process knowledge, particularly in product quality and response time. The data-driven optimization further enhances system performance by learning nonlinear process dynamics from historical operational data, resulting in noticeable improvements in energy efficiency, throughput, and operational stability. However, despite these advancements, neither the physics-based nor the standalone data-driven approaches are capable of simultaneously maximizing all performance indicators because each method has inherent limitations in adapting to continuously changing industrial operating conditions. In contrast, the proposed hybrid framework effectively combines the physical interpretability of first-principles models with the adaptive learning capability of artificial intelligence and continuous real-time process synchronization, enabling balanced optimization across multiple operational objectives.

The quantitative comparison shown on the right side of Figure 6 further confirms the significant advantages of the proposed framework over the conventional PID control strategy. Specifically, the proposed hybrid framework improves energy efficiency by 50.4%, indicating a substantial reduction in energy consumption while maintaining the desired operating conditions. Production throughput increases by 70.7%, demonstrating a significant enhancement in manufacturing productivity and production capacity. Furthermore, product quality improves by 18.3%, reflecting the framework's ability to maintain process variables closer to their optimal operating points and thereby reduce quality variation. The proposed framework also achieves a 64.2% improvement in response time, enabling faster corrective actions and quicker recovery from process disturbances. In addition, operational stability increases by 45.6%, confirming that the framework effectively suppresses process oscillations and maintains stable system operation under dynamic industrial conditions. Collectively, these improvements demonstrate that the proposed hybrid simulation framework provides a comprehensive optimization solution that simultaneously enhances productivity, product quality, energy efficiency, and process reliability without sacrificing system stability. The superior performance observed across all evaluation metrics validates the effectiveness of integrating physics-based process modeling, data-driven predictive analytics, real-time data synchronization, and intelligent optimization algorithms into a unified framework. Consequently, the proposed approach offers a highly promising solution for next-generation smart manufacturing systems, where adaptive, resilient, and sustainable process optimization is required to improve operational competitiveness, reduce production costs, and support the realization of Industry 4.0 and intelligent industrial automation.

The novelty of this study lies in the development of an integrated real-time hybrid simulation framework that combines physics-based process modeling, data-driven machine learning, real-time Industrial Internet of Things (IIoT) data synchronization, and intelligent optimization within a unified closed-loop architecture for dynamic industrial process optimization. Unlike previous studies that primarily focus on either physics-based simulation, standalone data-driven prediction, or offline hybrid modeling, the proposed framework continuously updates model parameters using live process data, enabling adaptive decision-making under rapidly changing operating conditions. Furthermore, the framework simultaneously optimizes multiple industrial performance indicators, including energy efficiency, production throughput, product quality, response time, and operational stability, rather than optimizing a single objective. The experimental results demonstrate that the proposed framework significantly outperforms conventional PID control, physics-based optimization, and data-driven approaches by achieving 50.4% higher energy efficiency, 70.7% greater production throughput, 64.2% faster response time, 45.6% better operational stability, and 18.3% improvement in product quality, while also attaining the highest prediction accuracy ($R^2 = 0.97$) and the lowest tracking error (ITAE = 5.47). These contributions provide a scalable and adaptive optimization framework that advances the implementation of intelligent digital twins and autonomous industrial process control, offering a practical solution for next-generation Industry 4.0 and smart manufacturing applications.

4. Conclusion

This study proposed a real-time hybrid simulation framework for dynamic industrial process optimization by integrating physics-based modeling, data-driven prediction, real-time data synchronization, and intelligent optimization into a unified closed-loop architecture. The experimental results demonstrated that the proposed framework consistently outperformed conventional PID control, physics-based optimization, and standalone data-driven approaches across all evaluated performance indicators. Specifically, the proposed framework achieved the lowest process tracking error (ITAE = 5.47), the highest prediction accuracy ($R^2 = 0.97$), and the lowest prediction errors (MAE = 1.76 and RMSE = 2.71), while effectively maintaining process stability under dynamic disturbance conditions. Furthermore, the framework reduced energy consumption by 50.4%, increased production throughput by 70.7%, improved product quality by 18.3%, enhanced response time by 64.2%, and increased operational stability by 45.6% compared with conventional PID control. These findings confirm that combining first-principles process knowledge with adaptive machine learning and real-time optimization significantly improves industrial process performance, prediction reliability, and control robustness. Therefore, the proposed framework represents a promising solution for intelligent digital twins, autonomous process control, and next-generation Industry 4.0 manufacturing systems, providing an adaptive, scalable, and energy-efficient approach for real-time industrial process optimization.

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