CHAPTER 6

Conclusion and Future Work

In this thesis, we examine the forms of industrial system coupling, the challenges encountered in optimal control across various coupling contexts, and propose a model-assisted optimization framework. Using TBM trajectory navigation, reflow furnace temperature field control, and fluid machinery safety control as case studies, we investigate specific strategies to address the primary challenges posed by coupling and achieve optimal control in different coupling scenarios. Building on the above research, this chapter summarizes the contributions of each section and outlines future research directions as well as potential application areas.

6.1 Summary

Chapter 1 provides an introduction to the research topic - industrial system coupling, optimal control, and model-assisted optimization. We present the research questions to be addressed, which include how to mitigate the impact of unobservable environmental states on decision-making and achieve optimal control in partially observable environments, how to establish an effective mapping between control objectives and control parameters based on system operational principles, enabling the efficient inversion of optimal control parameters with manageable computational overhead and how to design control algorithms for nonlinear systems composed of capacitive working media and industrial equipment, capable of eliminating system hysteresis and achieving safe, stable control.

Chapter 2 categorizes the industrial system coupling into three types: macro-scale system-environmental coupling, meso-scale inter-component coupling, and micro-scale system-working media coupling. We detail how environmental uncertainty transforms optimal control into a Partially Observable Markov Decision Process (POMDP), how internal component coupling creates high-dimensional, computationally expensive optimization landscapes, and how media coupling introduces nonlinearity and time delays that threaten system safety. To solve these challenges, the chapter introduces MAO as a crucial strategy, highlighting the roles of computer-assisted engineering simulation, data-driven, and physics-based modeling in providing the predictive capability and computational efficiency necessary for achieving accurate, safe, and adaptive optimal control in complex industrial settings. Finally, we establish a comprehensive framework for understanding and addressing the optimal control problem in coupling situation.

Chapter 3 addresses the optimal control problem in industrial systems and the environment coupled condition, using the precise trajectory navigation of Tunnel Boring Machines (TBMs) under partially observable geological conditions as case study.

We propose a novel three-layer hierarchical POMDP framework to decouple this complex decision-making problem. In the Policy Layer, a RL agent interacts with a specifically developed PCDM model to perform online learning and optimal path planning in a simulated environment. The Belief Layer employs a GRU network to infer the distribution of unobservable geological states by analyzing the temporal sequence of TBM operational states along the planned path. Finally, the Joint Decision Layer integrates outputs from the previous layers through a DNN to generate precise thrust force predictions. Experimental results demonstrate that this approach successfully achieves both path planning and accurate thrust prediction in simulated environments and, via transfer learning, with real-world data.

The framework provides a systematic, end-to-end solution with strong generalization capabilities for optimal control in industrial systems-environment coupling condition. In addition, the PCDM model proposed in this framework offers an efficient solution for simulating interactions between industrial systems and the environment. Most importantly, this framework effectively addresses our primary research concern of **RQ 1—How to mitigate the impact of unobservable environmental states on decision-making and achieve optimal control in partially observable environments**:

It demonstrates that optimal control under unobservable states can be achieved without explicit state reconstruction. By transforming the influence of hidden states from uncertain disturbances into compensable temporal effects through layered temporal causal inference, the framework proves that "resolving unobservability" does not necessitate "recovering hidden states." Instead, the belief layer captures the dynamic footprints of unobservable states in observable sequences, while the joint decision layer integrates raw observations with inferred beliefs to enable self-correcting control. Thus, unobservable states become conditionally redundant at the decision level—offering a fundamental shift from sensing-dependent optimization to causality-driven control. In this paradigm, the system no longer needs to know “what the world truly is”—only “how the world requires the system to respond.”

Chapter 4 solved the optimal control problem under the condition of coupling among components within industrial systems.

Taking reflow oven temperature field control as a case study, we develop a surrogate model-assisted digital twin framework to efficiently optimize control parameters for the multi-coupling reflow soldering process. A high-fidelity digital twin is calibrated via a regression-based loss function that enables precise gradient-descent identification of key aerodynamic parameters. To enable real-time, one-shot optimization, a non-iterative predictor is designed, combining a Transformer (to fuse process indicators and infer the complete temperature profile) with a CNN (to map the profile shape to optimal zone-specific control parameters). Experiments demonstrate the framework's high accuracy: the digital twin achieves precise temperature field simulation after calibration, while the integrated predictor achieves 98.90% accuracy in curve prediction and 99.36% in parameter mapping, enabling efficient closed-loop optimization with minimal computational cost.

The proposed method offers a novel approach for establishing interaction relationships among various components within a system. Moreover, the inverse-mapping surrogate model constructed using the Transformer-CNN algorithm provides a new strategy for reducing computational costs associated with increasing dimensionality and avoiding extensive iterative computations.

Addressing Core Research Question 2—**How to achieve accurate optimization of control parameters while avoiding the high computational costs of iterative searches in high dimensional spaces and expensive high-fidelity simulations**—the answer provided by this study is as follows:

By reconstructing inverse mapping and decoupling fidelity from efficiency, the optimization problem is transformed from "iterative search" to "one-shot solution."

The core breakthrough of this answer lies in the fundamental restructuring of the "optimization path." Traditional parameter optimization follows the paradigm of "forward simulation + iterative optimization": each parameter adjustment necessitates a high-fidelity simulation for evaluation. In high-dimensional spaces, the number of iterations grows exponentially with dimensionality, rendering computational costs prohibitively high. This study breaks away from this path dependency—rather than allowing optimization algorithms to "trial and error" repeatedly on simulation models, it enables the surrogate model to directly learn the inverse mapping from process objectives to control parameters. Once the mapping is established, optimization no longer requires any iteration: input the process metrics, perform a single forward propagation, and the optimal parameters are output instantly.

This restructuring is made possible by two levels of decoupling. The first is the task-level decoupling of fidelity and efficiency: the digital twin model is responsible for "fidelity," ensuring the physical accuracy of the data source at a minute-level computational cost, while the surrogate model is responsible for "efficiency," enabling millisecond-level responses for real-time parameter prediction. The two are connected through offline training and function independently during online deployment. The second is the physical embedding of the problem structure: the surrogate model is not a black-box fitting tool. Instead, it incorporates the causal chain of the production process—from process metrics to temperature profiles, and from profile characteristics to control parameters—as a prior structure embedded within the Transformer-CNN architecture. This allows the model to maintain high accuracy even with only a thousand-level sample size, significantly reducing data generation costs.

The broader significance of this answer lies in its revelation that, for industrial optimization problems involving expensive simulations and high-dimensional complexities, the bottleneck often lies not in algorithmic efficiency but in the formulation of the problem itself. When we redefine the question from "how to find the optimal parameters" to "how to directly compute the optimal parameters from the objectives," iterative search is no longer a necessary pathway. This framework demonstrates that precision and economy are not inherently conflicting objectives but can be simultaneously achieved through the correct restructuring of the problem.

Chapter 5 tackles the optimal control problem arising from strong coupling among industrial systems and working media, exemplified by the safe, coordinated control of centrifugal compressors. To overcome the challenges of system nonlinearity, time delays, and coupled variables that cause dangerous overshoot and surge risk, we propose a novel strategy. This strategy integrates a fast, physics-based Greitzer lumped-parameter model for real-time safety evaluation with the CMA-ES for online optimization of PID controller parameters. Experimental results demonstrate that this approach significantly reduces pressure and flow overshoot compared to conventional methods, ensuring smoother, safer operating point trajectories that stay farther from the surge boundary, thereby enhancing both safety and robustness without compromising adjustment efficiency.

To address the nonlinearity arising from capacitive media-system coupling, we employ evolutionary algorithms to develop a safety controller, as evolutionary computation demonstrates strong capability in handling nonlinear problems. The proposed controller also provides a novel perspective on safety control in scenarios involving coupling between industrial systems and working media.

Addressing the core research question—**How to design control strategy for nonlinear systems with capacitive working media, capable of eliminating system hysteresis and achieving safe, stable control**—the answer provided by this study is as follows:

Through a model-assisted online optimization framework that integrates “physically quantified safety boundaries” and “evolutionary optimization of control parameters,” system hysteresis is transformed from an uncontrollable disturbance into a compensable trajectory constraint.

The core breakthrough of this answer lies in the fundamental reframing of “hysteresis.” Traditional control approaches treat system hysteresis as a physical defect that must be eliminated, attempting to “catch up” with system response through more complex models or faster feedback. This study demonstrates that for systems such as centrifugal compressors with capacitive working media, hysteresis is an inherent dynamic characteristic determined jointly by mechanical inertia and gas compressibility—it cannot be eliminated, but it can be planned. Rather than applying post-hoc corrections to PID output, we pre-construct exponential approximation trajectories for pressure and flow at the command layer, enabling the controller to perform trajectory tracking rather than target step response, thereby fundamentally avoiding the overlay effects of multi-variable overshoot.

However, trajectory planning alone is insufficient to address the challenges of strongly coupled, nonlinear control. Optimal PID parameters vary significantly under different operating conditions, and there exists complex coupling between speed and valve control. To address this, the study introduces the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) to achieve online, efficient optimization of multi-variable controller parameters. This algorithm requires neither system decoupling nor gradient information; it adaptively adjusts the search direction by learning the covariance structure among parameters online, achieving rapid convergence in highly nonlinear coupled spaces.

The broader significance of this answer is as follows: For nonlinear industrial systems characterized by capacitive media, large inertia, and strong coupling, the challenge of control lies not in "speed," but in "stability." When the control objective is redefined from "minimizing response time" to "planning feasible trajectories within safety boundaries," hysteresis transforms from an adversary of control into an ally that can be cooperated with. The physical model quantifies the surge boundary as a dynamic constraint, and CMA-ES efficiently searches for optimal parameters within this constrained boundary—safe and stable control is not about racing against system inertia, but about charting a path for inertia that never exceeds the limit.

6.2 Future Work

Given the favorable outcomes achieved by the framework proposed in this thesis, we believe it can be further refined in future research and extended to a broader range of industrial applications. In this section, we will continue the discussion from three perspectives: coupling between industrial systems and the environment, coupling among components within industrial systems, and coupling between industrial systems and working media.

Coupling between industrial systems and the environment

For this part, future research will focus on investigating the confidence and confidence intervals of the decision outcomes produced by the hierarchical POMDP framework, in order to assess control safety, quantify reliability, and provide trustworthy references for control implementation. Subsequent work will also investigate the integration of advanced sensing technologies—such as real-time geophysical sensing data and computer vision systems—into the belief state updating process. Additionally, we will explore the impact of different look-back horizons on the GRU model, adaptively adjust its hyperparameters, and improve predictive accuracy. Furthermore, attention-based multi-scale feature fusion strategies will be developed to strengthen the model's capability to comprehend complex geotechnical patterns.

In industrial practice aspect, the proposed framework is expected to applied to additional real-world scenarios such as robotic navigation, autonomous driving, and UAV countermeasures to further validate its performance. The selection of robotic navigation, autonomous driving, and UAV countermeasures as future validation scenarios is not arbitrary (Adamkiewicz et al. 2022, Chib et al. 2024, Sherman et al. 2025). They represent a graduated series of testing environments where the problem of decision-making under partial observability is paramount. Robotic navigation typically involves state estimation and planning within geometrically complex but often passively dynamic environments. Autonomous driving intensifies this challenge by introducing a multitude of other intelligent agents whose future behaviors are uncertain and must be predicted. UAV countermeasures further escalate the demands by incorporating active adversaries who deliberately introduce deception and uncertainty. Applying the framework across this progression allows for a systematic evaluation of its core capability: to maintain and leverage a sophisticated belief state in the face of increasing environmental complexity and antagonism using time-series information.

Coupling among components within industrial systems

For this part, future work will focus on enabling bidirectional real-time communication for the digital twin model using surrogate models, as well as achieving long-term calibration of surrogate model parameters through continuous learning. The integration of active learning, Bayesian optimization, and other sampling strategies into the construction of inverse-mapping model datasets will also be considered, particularly given their potential to further enhance model accuracy and reduce computational time for the proposed method.

In practical applications, the proposed digital twin modeling and inverse-mapping surrogate model construction methods are expected to be applied to scenarios such as aircraft turbine blade parameter optimization, wind-turbine blade design optimization, and engine cooling-system design. These scenarios resemble the reflow furnace temperature-field control problem in that they involve complex inter-component interactions and intricate working mechanisms requiring high-fidelity simulation, which typically incurs substantial computational costs. By applying the proposed approach to such problems, it is anticipated that parameter optimization can be achieved with significantly lower computational overhead.

Coupling between industrial systems and working media

For this part, the primary theoretical advancements should focus on enhancing the framework's robustness, intelligence, and theoretical guarantees. Key directions include the deeper integration of the CMA-ES-based optimization with formal robust control theory, adaptive control, or safe reinforcement learning (Safe RL). This aims to provide provable stability and convergence guarantees under bounded model uncertainties and disturbances, moving from empirical validation to mathematically assured safety. Furthermore, the intrinsic time-delay and nonlinear coupling mechanisms could be more explicitly modeled and leveraged within the optimization objective, potentially by incorporating predictive safety filters or designing novel delay-aware cost functions for the CMA-ES to fundamentally address the root cause of overshoot.

For practical deployment and broader impact, applied research should target real-time adaptation, scalability, and hardware integration. A critical direction is developing lightweight, real-time variants of the CMA-ES algorithm or hybrid strategies that combine its global search capability with local gradient information for faster online convergence. The framework should be extended and validated across a wider spectrum of turbomachinery and complex industrial processes with multi-loop coupling, such as chemical reactors or multi-unit energy systems. Finally, research into seamless integration with Industrial Internet of Things (IIoT) platforms and edge computing architectures would be essential to transition the strategy from a simulation-based solution to a deployed, self-optimizing control system in live industrial environments.