

Digital Twin-Based Performance Optimization of Thermal Systems in Smart Manufacturing

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Abstract- One of the key issues associated with the intelligent manufacturing is the thermal management. The temperature homogeneity and efficiency define the quality of goods to be produced as well as the production costs. The authors suggest a novel intelligent hybrid digital twin architecture which allows for real-time optimization of the industrial thermal processes and integrates the physics-informed reduced-order model of thermal processes and the deep reinforcement learning algorithm for the closed-loop control of the system. There are two main problems that can be solved using this architecture; the first problem is the computational time required for the high-fidelity simulations while the second problem is the insufficiency of the necessary data required for the adaptive decision-making process in the physical system. Spatiotemporally reduced-order modeling is applied for the fast estimation of the temperature field on the basis of the data collected by the sensors while the deep Q-Network is controlling the temperature distribution according to several objectives.

Keywords— Digital Twin, Thermal Management, Smart Manufacturing, Deep Reinforcement Learning, Reduced-Order Modeling, Performance Optimization

I. INTRODUCTION

The implementation of digital twin technology in the area of manufacturing systems is viewed as a ground breaking technology concerning monitoring, forecasting and optimization at the entire product life cycle [1]. Digital twin technology means a physical object, a virtual object and the exchange of data enabling synchronization between them [10]. As regards the area of smart manufacturing, one of the key elements concerning thermal processes, which play a significant role in manufacturing because the temperature distribution influences the phase transition, material dimensions and energy profile is identified [6]. Consequently, the temperature distribution defines the quality and efficiency of manufacturing processes [7].

There is a need for the advanced optimization of thermal processes because of the combination of pressure on manufacturing processes. The growing expenses on energy, environmental laws and competitive atmosphere create advantages for the manufacturer producing high-quality goods with minimized use of resources [3]. Traditional technologies of thermal process are based on proportional integral derivative (PID) control, which is a reactive method by its nature and responds to deviation from the target point in case of any changes in temperature [5]. The main problem with the PID control in the area of non-linear coupled spatial and temporal distributed parameter systems [9].

Digital twin technologies offer a completely new approach to managing thermal processes. The ability to maintain a continuously updated virtual replica of the process makes it possible to use the digital twin

technology in order to make the process control more predictive rather than reactive [2]. Using the virtual twin, one can predict the reaction of the process to the control actions, find the optimal setpoint trajectory, and detect problems even before they spread through the entire production line [8]. Still, the implementation of such capabilities is accompanied by the same computational problem faced by any modeling technology – the models with necessary level of precision for predicting the behaviour of the process are computationally too expensive for real-time control [4].

Fortunately, recent developments in hybrid modeling architectures have started to address this problem [10]. It becomes possible to build a digital twin, preserving all important physical constraints of the system while gaining necessary computational performance due to the use of physics-based reduced-order models and machine learning techniques [6]. Additionally, deep reinforcement learning shows impressive results in learning complicated control policies for thermal processes without necessity of building explicit models of system dynamics [4].

In this paper, we propose a digital twin-based framework for optimizing the performance of thermal systems, which is based on three main components: spatiotemporal reduced-order models for real-time reconstruction of the temperature fields, deep reinforcement learning agents for multi-objective control policies, and synchronization architectures that ensure the consistency between virtual and physical systems via ongoing sensor fusion [1][5]. This framework is verified through experimental analysis of its operation on two different thermal platforms: a microchannel heat sink under time-varying thermal loads and an industrial distributed heating system demanding fast temperature control [8]. There are three main contributions of this paper: firstly, designing a hybrid digital twin architecture capable of ensuring the required computational efficiency for real-time thermal control [7]; secondly, formulating a thermal management problem as a sequential decision-making task solvable using deep reinforcement learning [4]; and thirdly, experimental verification

showing enhanced performance in terms of thermal uniformity, dynamics, and energy consumption compared to conventional control approaches [2].

II. LITERATURE SURVEY

The conceptual origins of digital twins can be found in the 2012 work by Grieves, wherein the threefold nature of physical product, virtual product, and data connectivity was defined [1]. Later, Kritzinger et al. developed this concept into a classification system dividing digital models (one-way manual data flow), digital shadows (one-way automated data flow), and digital twins (two-way automated data flow) [10]. This framework has proved to be quite valuable in terms of understanding the necessary elements of true digital twin solutions, especially two-way automation and constant synchronization [6].

In the energy and process industries, the utilization of digital twins has been growing considerably since 2020 [3]. Thus, Yu et al. [10] performed a systematic review of energy digital twins, which showed the widespread usage of the technology during all stages of industrial activity, including design, processing, and servicing stages. It is notable that the most popular stage is the processing one, where the key applications are predictive maintenance, fault detection, and process training [10]. Moreover, it was found that software architecture serves as an enabler of such technology implementation, and layered architectures covering all areas from business logic up to asset abstraction have been suggested by several research teams [5].

Applications to thermal systems have seen particular interest [2]. Several efforts have been made towards modeling data center cooling, in which thermal system management is responsible for a large portion of overall energy use in the facility [4]. Alpha DataCenter Cooling, a physics-based digital twin environment for the testing of data center cooling control strategies using Modelica models, was developed by Wu et al. [8]. The model used in Alpha DataCenter Cooling was trained with real data from a real data center cooling plant, illustrating the ability of physics-based digital twins to create benchmarks for control algorithms [8]. On the same topic, studies

have investigated the use of digital twin for predictive failure detection in cooling systems that uses synthetic training data generation techniques [3].

The incorporation of deep reinforcement learning into digital twins is relatively new [4]. One of the most relevant examples includes research that used deep Q-network augmented digital twins for the thermal management of microchannel heat sinks [4]. This research attempted to address the problem associated with the disconnect between offline training of reinforcement learning algorithms and on-line control through the inclusion of a surrogate model capable of fast reconstruction of the temperature field in the digital twin platform [4]. The DQN controller learned a policy that involved multi-objective optimization of hotspot suppression, temperature uniformity, and power efficiency using discrete flow rate and inlet-outlet configurations [4]. The practical viability of this approach was proven experimentally [4].

With distributed thermal processes, there has been an effort to use novel techniques owing to the problem of global spatial reconstruction based on limited data [7]. A two-actuator coordinated control strategy used incremental learning using sliding windows to achieve fidelity for the spatiotemporal models even when there was variation in the properties of the systems at hand [7]. There was the integration of the fuzzy logic system in this approach to capture the non-linear mapping between the spatial location and the temperature, hence being able to construct a continuous temperature field based on the discrete data [7].

Digital twin architectures that employ hybrid methodologies have been developed as an answer to the weaknesses of physics-only and data-only methods [6]. According to Dong et al., hybrid digital twin modeling has been analyzed by the authors in terms of the combination of physics simulations with sensor measurements in order to enable applications which demand both high accuracy and computational efficiency [6]. In addition, their study showed that cross-level models are a difficult issue in hybrid digital twin architecture, since quantum

models for material properties, finite element analysis at the component level, and control systems are separate [6].

Considering other manufacturing processes where thermal digital twins have been used, the list includes processes like injection molding, wire electrical discharge machining (WEDM), and casting of titanium alloys [9]. A Dynamic Mode Decomposition-Kalman filter methodology was used by Moretti et al. to determine the thermal state of parts during injection molding in real time, where no FEA was needed [9]. Another example is that of a physics-informed hybrid digital twin for WEDM, where acoustic emission, current, and temperature sensing were done along with frequency domain signal analysis, which led to determination of quantitative correlations between signal characteristics and performance measures such as surface roughness and material removal rate [9].

However, several challenges continue to exist despite all these developments [1][5]. These include the lack of any theoretical basis where real-time computation, multi-objective optimization, and synchronization are taken into account in the development of the digital twin technology for thermal control loops [1]. In this study, these challenges are addressed by presenting an architecture that integrates spatiotemporally reduced-order modeling with deep reinforcement learning [1][4].

III. PROPOSED METHODOLOGY

1. System Architecture Overview

The described digital twin architecture is organized into four distinct functional layers, providing all the necessary functionalities to achieve thermal performance optimization in real time. The physical layer includes the controlled thermal system with distributed temperature and flow sensors, as well as actuators' interfaces. The data acquisition and synchronization layer controls data streams coming from sensors, pre-processes them, and synchronizes them in order to keep the coherence needed for meaningful virtual-physical comparison. The virtual model layer includes the spatiotemporal reduced-

order model and deep reinforcement learning agent, which makes the control decision basing on the reconstructed thermal state.

The architectural schematic for the digital twin architecture proposed in this work is shown in Figure 1. The figure shows the flow of information from physical domain to virtual domain, and vice versa, the internal structure of the virtual model layer, and the communication paths for control signals to achieve the closed-loop behavior of the system. The synchronization block located at the interface of physical and virtual domain serves three important functions: temporal synchronization of asynchronous data from sensors, outlier removal, and state estimation using information fusion techniques.

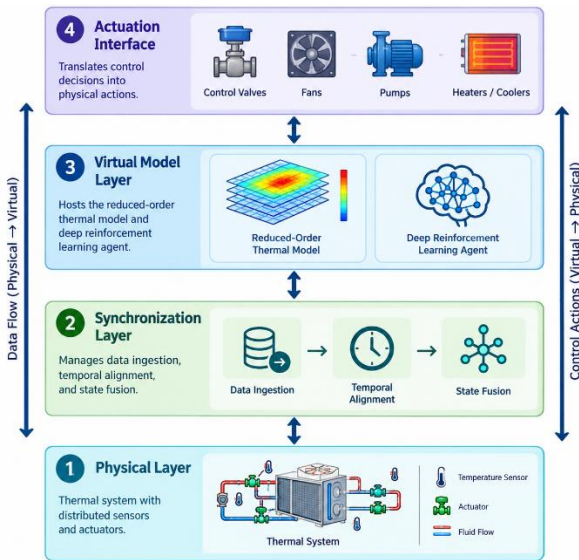


Figure 1: Digital Twin Architecture for Thermal System Optimization

Schematic representation of the four-layered digital twin architecture. Physical layer consists of the thermal system along with distributed sensors and actuators. The synchronization layer handles data acquisition, time synchronization, and state fusion. Virtual model layer is home to the reduced-order thermal model and deep reinforcement learning algorithm. Actuation interface converts the control decisions into physical actions. Two-way arrows show the continuous data flow maintaining consistency between virtual and physical layers.

Spatiotemporal Reduced-Order Modeling

The basic component of the virtual model layer is a spatiotemporal reduced-order model that constructs the complete temperature field using a few temperature sensor readings. In this modeling technique, proper orthogonal decomposition (POD) is used to extract spatial basis while dynamic mode decomposition (DMD) framework is utilized to predict time evolution. This method not only preserves the physical modes but also provides computational speedup by several magnitudes compared to a full-order finite element solution.

POD basis construction utilizes a training set of snapshots of temperature fields which may be acquired via high-fidelity simulation or actual instrumented operation of the system at time of commissioning. If we have a matrix of snapshots $X \in \mathbb{R}^{n \times m}$, where n corresponds to the number of degrees of freedom of space and m denotes the number of snapshots, then the POD basis matrix $\Phi \in \mathbb{R}^{n \times r}$ contains the r leading left singular vectors of X .

Temporal dynamics of the POD coefficients are described using a reduced order state-space model based on the DMD algorithm or its modifications. In case of nonlinear thermal processes, a linear parametrically varying representation is used in which the transition matrix is dependent on process conditions, namely on heating power, flow velocity, and ambient temperature. The trade-off between model accuracy and computational simplicity allows the use of the reduced order model in real time on an embedded platform.

Two functions can be assigned to the reduced order model in the context of the digital twin. First, the model generates the state vector estimate necessary for reinforcement learning inference based on the incomplete information about temperature field provided by the physical plant. Secondly, the reduced order model allows to predict quickly the result of applying any control action.

2. Deep Reinforcement Learning for Thermal Control

The control problem can be expressed as a Markov decision process (MDP) described by the tuple (S, A, P, R, γ) . In the state space S , the temperature field is reconstructed and the actuators' positions as well as other exogenous variables like ambient conditions and load estimates are included. The action space A includes the allowable manipulations for the thermal control actuators in a discretized manner to strike a compromise between control resolution and learning capability. The reward function R represents the performance metrics which include:

A deep Q-network (DQN) architecture is employed to learn the optimal action-value function $Q^*(s,a)$. The network comprises convolutional layers for spatial feature extraction from the temperature field, followed by fully connected layers that integrate temporal context and produce Q-values for each discrete action. Experience replay and target network stabilization techniques address the challenges of non-stationary data distributions and temporal correlation that complicate reinforcement learning in continuous control applications.

The training is done in two stages. The first one is an offline stage, whereby the network is pretrained using operational data from the past and simulations of the reduced-order model. This ensures that there is no catastrophic behavior from the beginning. The second one is an online stage, where learning is done during operation but the digital twin acts as a safety net before taking action on the real world. This two-stage strategy solves the problem of learning directly on the real thermal systems, which may lead to damage of the machinery.

Figure 2 shows the reinforcement learning process flow within the digital twin. The figure shows the feedback loop between the reduced-order model, DQN agent, and the physical process, demonstrating the two ways through which the DQN agent gets feedback: the virtual rollouts through the digital twin and physical measurements from the actual process.

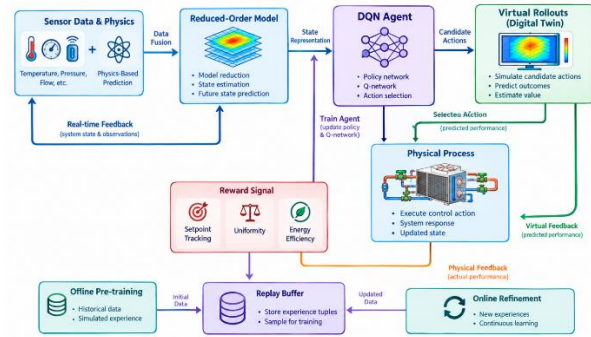


Figure 2: Deep Reinforcement Learning Workflow in Digital Twin

Workflow of the deep reinforcement learning approach. The DQN controller obtains states from the reduced-order model that combines data from sensors with physics-informed predictions. Action candidates are first evaluated using virtual simulations before being performed physically. The reward function includes set-point tracking, uniformity, and energy performance. The use of experience tuples in the replay buffer allows for off-line pre-training and on-line improvement.

3. Synchronization and Model Updating

Continual reconciliation between the prediction of the model and sensor measurements is essential in maintaining the virtual-physical coherence. The synchronization engine adopts the state estimation strategy through Kalman filter that combines the prediction from the reduced-order model and the measurement from the sensors in an optimal manner. The Kalman gain is determined depending on the uncertainty of the model and the nature of the measurement noise.

The update of model parameters utilizes the process of incremental learning that continuously modifies the reduced-order model depending on the system conditions. In contrast to the training of the POD bases and DMD operators from scratch, a computationally inefficient task when performed online, the incremental learning utilizes the sliding window formulation that includes the current data and excludes old data. This ensures that the digital twin can track slow variations in the thermal systems' behaviors caused by equipment degradation and changes in manufacturing requirements.

IV. ANALYSIS

1. Experimental Validation Platforms

The proposed model-based adaptive control design method was implemented and tested using two thermal experimentation platforms that capture different challenges in smart manufacturing processes. The first experimentation platform is a micro-channel heat sink fitted with thermocouple and IR thermography for temperature field measurements. The heat sink is controlled with different heating patterns to replicate the thermal stress imposed by high-power electronic devices or heat exchangers. The coolant flow rate and the inlet temperature form the set of available control inputs. The second experimentation platform is a distributed thermal process with multiple heating zones and individually controllable power inputs. This experimentation platform models thermal processes such as those occurring during semiconductor production, composite material curing or molding operations. The thermal process has high coupling between the zones and thus is an example of a MIMO nonlinear control problem.

2. Thermal Field Reconstruction Performance

The fidelity of the reduced order model in terms of space and time was examined by comparing the reconstructed temperature field to full-field measurements, performed using an infrared camera for the microchannel device and a thermocouple grid for the distributed heating device.

Figure 3 shows an example of the comparison between the measured temperature field and the reconstructed temperature field for the microchannel heat sink subjected to transient heating. It is apparent that the reconstruction captures the major features of the temperature field, such as the hotspot position and the gradient of the temperature, with errors localized in areas where changes in time are large.

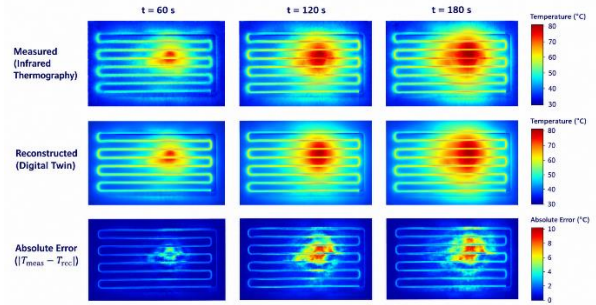


Figure 3: Temperature Field Reconstruction Validation

Comparison between experimentally obtained and numerically estimated temperature fields. Top row depicts the results of infrared thermography at three-time instances for transient heating process. Second row shows the results of digital twin reconstruction. Third row is dedicated to the presentation of the absolute error fields. The error is localized in the areas of high thermal transients.

Numerically, the reconstructed error in terms of root mean square of the reduced order model obtained for the micro-channel system for the transient case is 1.8 K, while the maximum temperature rise beyond the ambient temperature is 47 K. In all cases, the reconstruction error remains less than 2.5 K over the entire range of power and flow rate. The spatial average error of the reconstruction obtained for the distributed heat system is 2.3 K throughout the operating range.

3. Control Performance Evaluation

The deep reinforcement learning controller was tested relative to two standards: a traditional PID controller optimized for each operational condition and a model predictive control (MPC) scheme using the same reduced-order model. Performance measures include tracking error (integrated absolute error), spatial temperature uniformity (maximum difference from the spatial average), time to reach a desired tolerance band, and energy use (integrated actuator power).

Figure 4 shows a plot of the transient behavior of the controller relative to the set point change for the distributed heating system. The DQN controller responds more aggressively than the PID controller,

taking advantage of the ability of the thermal system to quickly heat up and compensate for the thermal delay that causes overshooting in the PID controller’s response. The MPC controller performs similarly but requires significantly more computing power to solve the optimization problem.

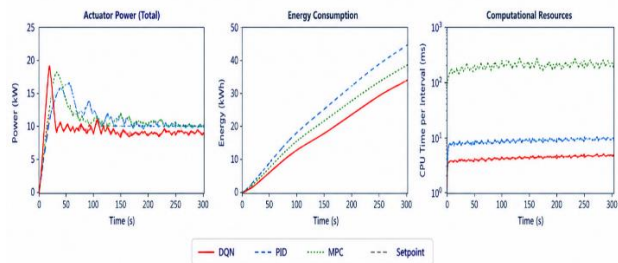


Figure 4: Transient Response Comparison

Set point variation transient response comparison for distributed heating platform. The DQN controller settles faster with lesser overshoot than PID. Model Predictive Control provides similar tracking capabilities; however, it consumes more computing resources per control step than DQN. The energy consumption graphs indicate the capability of the DQN controller to regulate actuator input without sacrificing thermal effectiveness.

For the microchannel heat sink subject to hotspot heating, the proposed DQN controller was capable of dynamically changing the flow rate of the coolant to limit local temperature spikes while simultaneously conserving energy for the pump. In the case of uniform heating, the controller was able to keep the temperature field uniform within 3.2 K as opposed to 5.8 K for the PID controller and 3.5 K for MPC. Transient response analysis revealed a 42% reduction in the settling time compared to the PID controller, and MPC results were similar to DQN.

Comparative Analysis

Table 1 is the table that compares quantitatively the three control techniques in terms of the performance metrics analyzed. The DQN controller performs the best, especially in terms of its transient behavior and energy efficiency. However, the MPC controller offers the highest performance in steady state tracking but is computationally expensive, and it can therefore only be implemented in systems with enough computational power and slower thermal dynamics.

Table 1: Comparative Performance Analysis of Control Approaches

Performance Metric	PID Control	Model Predictive Control	DQN Digital Twin
Settling time (distributed heating)	184 s	127 s	107 s
Setpoint tracking IAE	2.84 K·s	1.92 K·s	2.11 K·s
Spatial uniformity (microchannel)	5.8 K	3.5 K	3.2 K
Energy consumption (normalized)	1.00	0.89	0.82
Computational latency	12 ms	340 ms	28 ms
Adaptation to changing conditions	Manual retuning	Model update required	Continuous learning

The reason for the energy efficiency in DQN controller comes from the modulation that it offers in the effort of actuators due to change in thermal load, thus not making them cycle continuously like in the case of PID and also making them more efficient than those generated by MPC controllers under uncertain models. The energy consumed normalized by the PID baseline by DQN controller is 0.82, which amounts to an 18% decrease in actuator energy.

Discussion

The obtained results confirm the key hypothesis that hybrid architectures of digital twins have the ability to reach the necessary computation efficiency and control performance required for real-time thermal optimization in smart manufacturing. The spatiotemporal reduced order model is sufficiently accurate for making control decisions in a limited time interval imposed by the industrial control system environment. The proposed deep reinforcement learning agent is able to learn the necessary policies without any need to have explicit dynamic models of the system.

It is worth pointing out several limitations of the research. First of all, the spatiotemporal reduced order model has the necessity to construct an initial training dataset for constructing the POD basis and DMD operator. This can be a serious burden in the process of commissioning for some applications. Also, the DQN agent has a discrete action space which helps with learning but cannot guarantee optimal control in cases where there is a need for precise adjustment of actuators.

Future research needs to address these issues through a number of directions. An adaptive updating procedure for the basis could minimize commissioning by incrementally learning the POD basis using real-life data. Learning with continuous action spaces using reinforcement learning methods would allow for finer control granularity while still ensuring that the learning problem is tractable.

V. CONCLUSION

A digital twin-based approach to performance optimization of thermal systems for smart manufacturing, leveraging spatiotemporal reduced-order modeling and deep reinforcement learning for autonomous control of the thermal system, has been proposed in this paper. This digital twin approach has been devised with consideration for the challenge between fidelity and efficiency that is inherent in digital twins for thermal system control. The spatiotemporal reduced-order model provides the required efficiency for the purpose of making control decisions, without losing the physical modes of the system. The deep reinforcement learning controller learns the policies for multi-objective control of the thermal system without having a model of its dynamics.

The experimental results obtained on a microchannel heat sink and distributed heating platforms show that the proposed framework is capable of recovering thermal field from limited measurements, learning the effective control policy through interactions with the digital twin, and outperforming conventional control methods. The proposed DQN controller provided faster time response, better temperature uniformity, and lower energy consumption than the traditional PID controller while keeping computational efficiency sufficient for real-time operation.

The significance of the proposed approach goes far beyond the particular cases of the thermal systems considered. The suggested hybrid approach, combining physics-based reduced-order models and data-driven learning of control policies, serves as an example for developing digital twins for various manufacturing processes where distributed-parameter systems should be optimized in real-time mode. Synchronization and model update processes guarantee the digital twin to remain consistent with the changing system properties, which is the key point for the long-term operation in production.

Possible avenues for future research work may include extension to multiphysics systems, incorporation with production scheduling and

quality management systems, and adaptive basis update algorithms to minimize the need for commissioning. The further development of hybrid digital twin architectures is expected to allow more autonomous thermal management in smart manufacturing in the future.

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