SELF-ADAPTIVE DIGITAL TWINS FOR REAL-TIME OPTIMIZATION OF THERMAL POWER SYSTEMS

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ABSTRACT

The advancement of modern energy systems increasingly depends on the development of self-adaptive Digital Twins (DTs) that integrate real-time monitoring data for dynamic model updating. Traditional reliance on static Regulatory Technical Documentation (RTD) introduces significant inaccuracies, as it does not reflect actual operating states or gradual equipment degradation. To address this, we propose a framework for constructing intelligent, self-adaptive digital twins that continuously update energy reference performance characteristics (RPCs) based on live data. The presented approach enables the creation of DTs that evolve in parallel with the physical system, ensuring high fidelity between the virtual and real assets. By implementing algorithms for intelligent parameterization, the digital model captures changes in equipment condition and operational constraints, providing an accurate and continuously updated representation of combined heat and power plants (CHPPs) assets. Experimental validation on industrial data shows that this self- adaptive modeling process drastically improves accuracy, reducing deviations between calculated and actual parameters from 17.4% to 0.7% for turbine technological minimum, and from 7.9% to 1% for unit fuel consumption. This work demonstrates that self-adaptive DTs, capable of monitoring-based updating of performance characteristics, are a promising direction for developing digital models that remain aligned with real-world conditions. Such DTs provide a robust foundation for advanced forecasting, reliable decision support, and sustainable operation of complex energy systems.
Keywords: digital twins, self-adaptive systems, intelligently updated energy characteristics, real- time monitoring, combined heat and power plants, optimization

1 INTRODUCTION

The adoption of Digital Twins for modeling complex industrial and energy systems has become critical for modern industrial digitalization, supporting advances in computational methods, simulation technologies, and intelligent control aimed at enhancing operational efficiency, reliability, and safety (as in Heluany & Gkioulos (2024) and Peterson et al. (2025)). A DT is a high-fidelity virtual counterpart of a physical asset that integrates geometry, behavioral models, and lifecycle information into a unified computational framework, enabling dynamic simulation, predictive analysis, and decision support (as in Tao et al. (2019)). As a core component of Industry 4.0 (as in Bongomin et al. (2024) and Liu et al. (2023)), DTs are increasingly transformative in the energy sector, where they enable large-scale data-driven optimization, adaptive modeling, and intelligent automation (as in Zhou et al. (2024) and Zhang et al. (2025b)).

CHPPs are critical infrastructures where unscheduled shutdowns for inspection or diagnostic experiments are not feasible due to high economic and technical risks (as in Zhang et al. (2025a)). In this context, DTs provide a computationally robust alternative by enabling continuous visualization of process states, interactive simulation of plant operation, and enhanced safety for both equipment and operation staff [19]. The fusion of physics-based models with real-time monitoring streams establishes a closed-loop digital environment that supports perpetual state estimation, anomaly detection, operational optimization, and early fault prediction (as in Lei et al. (2022)).

Nevertheless, many implementations that are referred to as "digital twins" are, in practice, static computational models constructed from digitized RPCs from RTD. Such simplified models lack adaptive mechanisms for representing equipment degradation, varying operational constraints, or dynamic process behavior, which leads to significant discrepancies between the physical system and its digital representation. This mismatch produces substantial errors in computing key performance indicators (KPIs), thereby undermining decision support for production planning, maintenance scheduling, and market operations (as in Wang et al. (2020)).

Current approaches for evaluating techno-economic KPIs in CHPPs remain largely dependent on RPCs. However, RTD provides only limited computational coverage of operating regimes, excluding non- standard circuit configurations, partial equipment outages, and degradation-induced parameter changes (as in Wan et al. (2024)). As a result, RTD-based EPCs cannot reliably characterize the evolving state of equipment or provide the robust inputs required for accurate techno-economic planning. Manual correction and episodic recalibration are possible but represent inefficient, non-scalable workflows incompatible with modern requirements for continuous digitalization.

This paper addresses these limitations by introducing a monitoring-based self-adaptive DT framework that enables intelligent and automated updating of energy performance characteristics (EPCs) through continuous online data integration. The main contributions are:

1. Formulation of progressive computational strategy for EPC updating – full construction – adapted to different levels of data availability.
2. Development of a self-adaptive algorithmic pipeline for intelligent EPC construction and real-time model recalibration.
3. Extensive experimental validation on industrial datasets, demonstrating significant reductions in estimation errors for key operational parameters compared with traditional RTD-based calculations.

2 Related Work

2.1 Digital Twins in Thermal Power Generation

The concept of a Digital Twin might be divided into a Digital Twin Prototype (DTP), used in equipment design, and a Digital Twin Instance (DTI), which represents an operating asset. Both function within a Digital Twin Environment (DTE), an integrated, multi-domain space connecting physical systems with digital models for predictive and interrogative analyses (as in Grieves & Vickers (2017)).

Another classification distinguishes Digital Models (DMs), Digital Shadows (DSs), and Digital Twins (DTs), where a true DT is defined by real-time bidirectional data exchange combined with forecasting and optimization capabilities (as in Lindner et al. (2023)) . The Reference Architecture Model Industry 4.0 (RAMI 4.0) provides a standardized framework, structured along three dimensions: hierarchy levels, life cycle aspects, and categories of description. Within this framework, the digital twin maintains a continuous link between the physical and virtual asset throughout its life cycle. A central element of RAMI 4.0 is the Asset Administration Shell (AAS), which acts as a standardized digital representation of assets. However, some researchers emphasize that the AAS often functions more as a digital shadow, since it does not inherently provide simulation or control functions, distinguishing it from a fully intelligent twin (as in Deuter & Pethig (2019) and Lindner et al. (2023)).

The development of a CHPP digital twin usually begins with the construction of a mathematical model of plant processes, which then becomes the basis for simulation and control. The choice of modeling methodology and tools depends on the tasks at hand and data availability. Studies report both simple analytical models and advanced numerical simulations implemented in specialized platforms. Widely used tools include MATLAB/Simulink (as in Gao et al. (2024)) and ANSYS (as in Liu & Bansal (2024)) for modeling combustion, heat transfer, and fluid dynamics relevant to boilers and heat exchangers. Certain ANSYS packages also simulate aerodynamics and electrical processes. Alongside industry-specific solutions such as GE's PREDIX (as in Smith et al. (2024)), Rotek's "Prana" (as in Lee et al. (2022)), and the "United Cycle" platform (as in Romanov et al.

(2003)). Despite their variety, these solutions are mostly static, updated rarely in practice, which leads to growing discrepancies between models and real plant behavior under wear, technological changes, or shifting operating modes.

To overcome these limitations, industrial DT frameworks often adopt a three-layer architecture: the physical layer (sensors and actuators), the digital layer (models and analytics), and the cybernetic layer (forecasting, control, visualization) (as in Xie & Wang (2022)). Hybrid architectures that combine physics-based (white-box) models with machine learning (black-box) models, such as the HT-TPP framework (as in Ghita et al. (2022)), improve both scalability and predictive capacity. Furthermore, advanced monitoring algorithms like Autocorrelation Feature Analysis (AFA) reduce computational complexity while increasing reliability of fault detection, and integration with deep learning extends DT applications to predictive maintenance (as in Daniell et al. (2024) and Sleiti et al. (2022)), multi-objective optimization of efficiency and emissions (as in Wang et al. (2024)), and sustainability areas such as carbon capture, utilization, and storage (as in Zhang et al. (2022)).

Despite these advances, most DT systems still rely on manual or periodic calibration, limiting autonomy and accuracy under dynamic operating conditions. Current digital twin systems often depend on manual calibration, limiting their adaptability. They typically lack automated updating strategies and struggle with dynamic conditions. This reduces their long-term accuracy and autonomy.

To address this, we propose a self-adaptive digital twin framework that continuously updates energy characteristics using real-time equipment data. Our solution enables full model reconstruction and integrates directly with diagnostic systems. Industrial validation confirms high accuracy in performance indicators and sustained alignment with physical assets.

2.2 The RTD Restrictions Problem

Traditional EPCs rely on RTD, which lacks continuous updating mechanisms. This leads to outdated PCs and inaccurate techno-economic indicators. Modern CHPP equipment operates under multiple technical constraints influenced by plant configuration and condition [26], including maximum electrical outputs, thermal extraction loads, boiler limits, and permissible ranges for auxiliary systems. Since CHPPs frequently operate in modes not covered by RTD, discrepancies arise between normative and actual states. Key limitations include: unaccounted technical constraints, missing data for non- standard configurations, and reliance on degraded design specifications. Consequently, static regulatory models introduce significant errors in KPIs, reducing operational and commercial efficiency. While monitoring methods detect deviations, they do not update PCs systematically, highlighting the need for self-adaptive systems.

Two case studies demonstrate these limitations: one estimates the technological minimum of a T-123/130-130 PR2 turbine, and another evaluates fuel consumption of a CCGT-180T unit. Both show substantial discrepancies between RTD-based calculations and actual performance, leading to inaccurate operational parameters.

3 Methodology

3.1 Information System Architecture

The information system architecture employs a multi-layered framework where data flows continuously from physical equipment to analytical modules through a central digital twin. Sensor data from turbines, boilers, and generators – including pressure, temperature, and power metrics – is collected and preprocessed by a SCADA system before being integrated into the twin. Initially configured using normative documentation, the digital twin operates as a physics-based model rooted in thermodynamic principles.

Its defining capability is a self-adaptive parameters update mechanism, driven by a Java-based algorithm. This system continuously compares real-time SCADA data against baseline values, detects operational drifts caused by equipment wear or mode changes, and autonomously adjusts model parameters – from localized corrections to full recalibration. The output comprises updated energy characteristics and key performance indicators, delivered via visualized reports to support operational decision-making, maintenance scheduling, and efficiency optimization. By enabling

closed- loop feedback between physical assets and their digital counterparts, this architecture eliminates the inaccuracies of static models and maintains precision throughout the operational lifecycle.

3.2 DIGITAL TWIN DEVELOPMENT FOR THERMAL POWER PLANTS

The proposed digital twin is based on a validated computational model of the thermal power plant, developed using the specialized "United Cycle" CAD system (as in Romanov et al. (2003)) and supplemented with digitized technical documentation. Transition from a static model to an operational digital twin is achieved through bidirectional SCADA integration, enabling real-time synchronization with the physical plant.

The system continuously aligns the digital twin's parameters with actual equipment states through automated, self-adaptive updates driven by streaming monitoring data. Monitoring calculations are performed every five minutes using SCADA-collected data that undergo preprocessing – including time- averaging, validation, correction, and reconstruction of missing values based on physical constraints. Following simulation, key performance indicators are derived and stored for visualization and decision support. Analysis of accumulated data tracks equipment characteristic changes over time, enabling automatic reparameterization.

Before deployment, the computational model undergoes rigorous validation against historical operational data, with independent verification of source code and algorithmic logic to ensure accuracy and reliability. The modeling workflow follows a structured three-phase approach:

1. Graph-based model construction, where the plant's topology is represented as a directed graph of interconnected components;
2. Model parameterization in which physical and operational characteristics are assigned to each component;
3. Mode simulation, where operational scenarios are executed by the simulation engine using real-time or scenario-specific input parameters.

3.3 FULL SELF-ADAPTIVE INTELLIGENT CONSTRUCTION OF ENERGY PERFORMANCE CHARACTERISTICS IMPLEMENTATION

Full self-adaptive intelligent construction of energy performance characteristics builds energy characteristics from scratch using a fully updated digital twin, eliminating dependence on RPCs. This method exemplifies the paradigm of continuous self-adaptive intelligent modeling, where characteristics are derived from a systematic exploration of feasible operating modes constrained only by physical and operational limits.

The primary advantages of this approach include:

– Accurate determination of technological minimum and maximum operating conditions;
– Precise assessment of the steam turbine unit's (STU) maximum feasible heat output;
– Correction of inaccuracies present in normative technical documentation;
– Consideration of the actual equipment condition, as well as technical and technological constraints.

This algorithm is illustrated in figure 1. The process for constructing the Gross Specific Heat Rate (GSHR) for electricity generation begins with preparation, including equipment data collection and parameter definition. This is followed by selecting a stable operational mode from monitoring data to serve as the basis for digital twin updating. The twin then undergoes self- adaptive adjustment to align with actual plant behavior. Next, boundary identification determines maximum heat output and technological power limits, calculating GSHR at critical points. Interpolation computes GSHR values across intermediate power levels for each thermal load curve. Finally, results are processed and organized into standardized reports for visualization and decision support.

During the GSHR characterization preparatory phase, initial model conditions are established using regulatory documentation and operational constraints. Key parameters include the time window for identifying stable operational modes and the thermal load discretization step for both heating and industrial steam extraction.

The digital twin undergoes automatic updates by identifying the longest stable operational mode within the specified timeframe. Stability criteria require electrical and thermal loads to remain

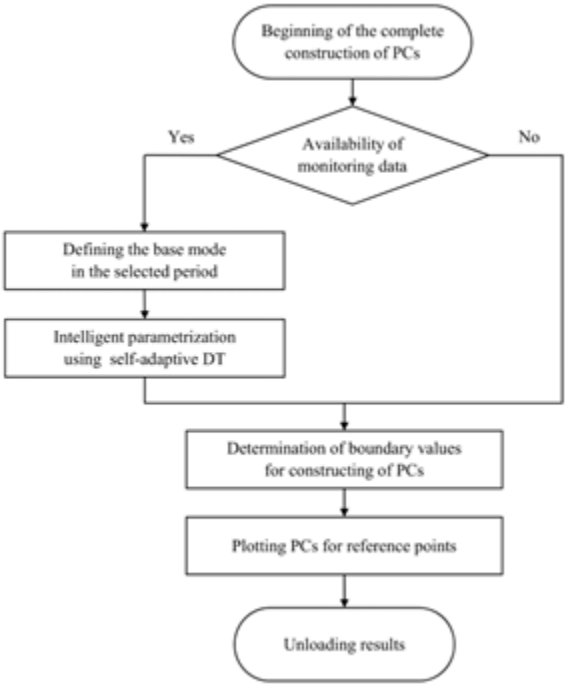

Figure 1: The algorithm for the full self-adaptive intelligent construction of energy performance characteristics of a digital twin based on monitoring data

within defined bounds for at least 30 minutes while meeting equipment safety limits and thermal balance requirements. Qualified data then drives the twin's self-adaptive reparameterization. The process begins by determining maximum feasible thermal load at specified steam extraction pressures through iterative reduction from upper bounds (Q_{max}), respecting equipment limitations. Intermediate load levels are generated by discretizing the [Q_{min}, Q_{max}] range using defined step sizes (dQ). Subsequently, boundary electrical outputs and corresponding GSHR values are calculated for thermal load extremes. Maximum electric output for each thermal load is determined by iteratively reducing live steam flow from maximum values (G_{max}) at the turbine inlet using step sizes (dG). At higher thermal loads, electric output is constrained by maximum steam throughput, while at lower loads it's limited by natural pressure increase in extraction lines. The algorithm shown in figure 2

The electric loads at the left boundary of the control range, corresponding to a specific heat output and gross specific heat rate for electricity generation, are determined by iteratively increasing the steam mass flow to the condenser, starting from the minimum ventilation steam bypass. Once the regulation range boundaries – technological minimum and maximum electric output – for a given thermal load are established, the interval is divided into equal segments. For each segment, the corresponding gross specific heat rate for electricity generation is calculated.
Finally, all computed data are organized and formatted into standardized reports, which include both tabular summaries and visual plots of the energy characteristics, providing a comprehensive view for analysis and decision support.

4 Experimental Evaluation Metrics

Two metrics were used to evaluate accuracy and effectiveness of the proposed approach:
1. Relative deviation based on RTD calculations (δ_{RTD}): this quantifies the difference between equipment performance indicators calculated using RTD and the actual values obtained from

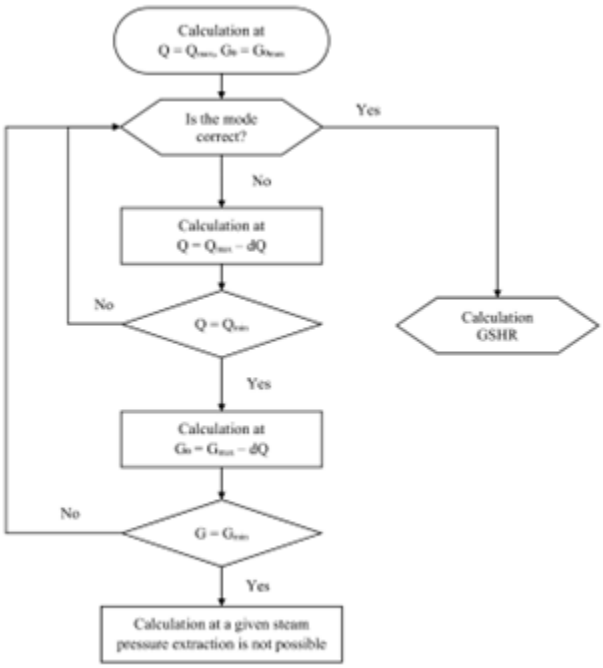

Figure 2: Algorithm for determining the point of maximum thermal load for a turbine unit: Q – heating extraction load, Q_{max} / Q_{min} – maximum / minimum steam extraction for cogeneration needs loads, G_0 – live steam flow to the turbine inlet, G_{max} / G_{min} –maximum / minimum steam flows, dQ / dG – thermal / steam flow step sizes.

SCADA monitoring, highlighting the gap between the assumed state in RTD and the real operational state of the equipment:

$$\delta_{\text{RTD}} = \frac{|P_{\text{RTD}} - P_{\text{FACT}}|}{P_{\text{FACT}}} \cdot 100\%; \tag{1}$$

2. Relative deviation based on DT calculations (δ_{DT}): this represents the discrepancy between performance indicators computed by the intelligently updated digital twin and the real-time values recorded by SCADA, showing how accurately the digital twin reflects the actual equipment state.

$$\delta_{\text{DT}} = \frac{|P_{\text{DT}} - P_{\text{FACT}}|}{P_{\text{FACT}}} \cdot 100\%; \tag{2}$$

5 EVALUATION

5.1 Case Study 1: technological minimum estimation

Consider Case Study 1, which examines the use of the fully intelligent updated energy characteristic to determine the technological minimum of a T-123/130-130 PR2 steam turbine. The main operating parameters are: generator terminal power – 68.1 MW, steam extraction pressure – 1.0 kgf/cm^2, and total heat load from district heating water heaters and domestic hot water boilers – 130 Gcal/h. According to the RPC, the technological minimum of the turbine under this operating mode is 79.5 MW, and after power adjustment, it is 68.55 MW. Based on the updated characteristics generated within the information system, the actual regulation range for this heat load is determined to be from 68.75 MW to 123 MW.

T The combined graphs of the gross specific heat rate for power generation are shown in figure. 3. The minimum power level indicated by the RTD for this operating mode exceeds the actual value by nearly 12 MW (δ_{RTD} = 17.4%), whereas the regulation range derived from the updated

characteristics aligns almost perfectly with the real operational value (δ_{DT} = 0.7%).

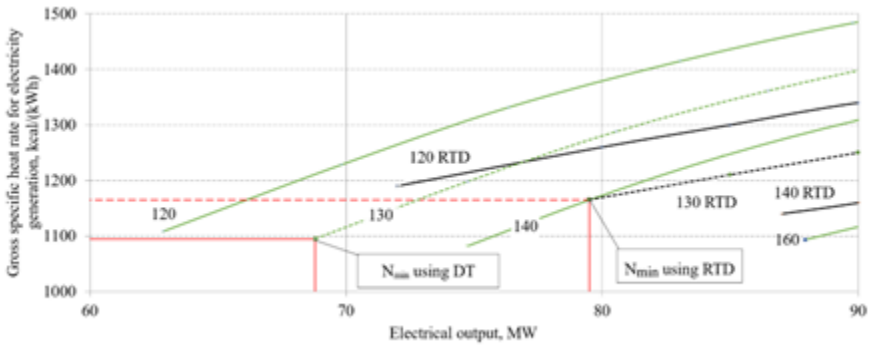

Figure 3: Determination of technological minimum for T-123/130-130 PR2 in single-stage mode at 1.0 kgf/cm^2 in the steam extraction line: Black – RTD data, Green – updated EPCs.

5.2 Case Study 2: Fuel Consumption Estimation

The second case study demonstrates the use of the intelligently updated energy characteristic to determine fuel consumption for a combined-cycle power unit CCGT-180T. The main operating parameters: generator terminal power – 42.9 MW, steam extraction pressure – 1.0 kgf/cm^2, and total heat load from district heating water heaters and the boiler condenser cooler – 90 Gcal/h. According to the RPC, the gross specific heat rate (GSHR) for electricity generation under this mode is 1385 kcal/kWh (obtained via curve extrapolation, as the target operating point lies outside the characteristic construction range). By contrast, digital simulation using the information system yields a GSHR of 1660 kcal/kWh. The comparison of characteristic curves is shown in figure 4.
Consequently, the fuel consumption for the CCGT unit, calculated using RTD data, amounts to 35.55 thousand Nm^3/h (δ_{RTD} = 7.9%), whereas using the updated energy characteristics, it is 38.2 thousand Nm^3/h (δ_{DT} = 1%), demonstrating a significantly higher accuracy with the intelligent digital twin.

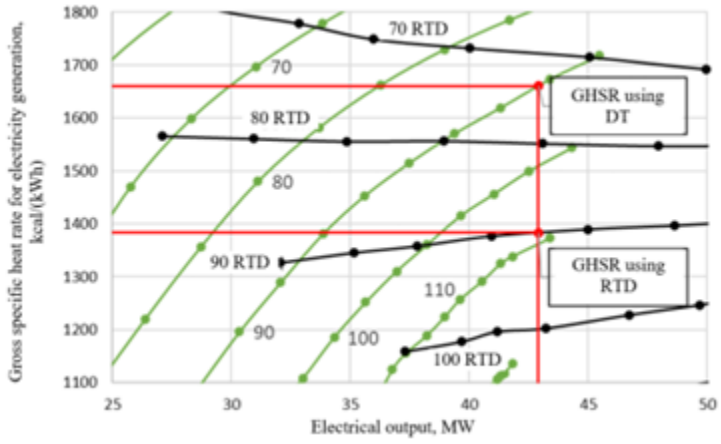

Figure 4: Determination of the gross heat specific rate for electricity generation for T-50/64-7.4-1.2 for the operation mode of the CCGT-180T for a total heat load of 90 Gcal/h for a two-stage mode at 1.0 kgf/cm^2 in the steam extraction line: black – RTD data, Green – updated EPCs.

6 THREATS TO VALIDITY

External Validity: The primary threat concerns the accuracy and reliability of SCADA data. Despite preprocessing, measurement errors, transmission failures, or sensor desynchronization could affect stable mode selection and model updating. The accuracy of the underlying "United Cycle" model depends on correct initial parameterization; simplifications or inaccuracies in equipment descriptions may introduce systematic errors. These are mitigated through multiple calculations and statistical analysis but cannot be entirely eliminated.
Internal Validity: The study used data from CHPPs with unit architecture and modern SCADA. This may limit the generalizability of results to plants with cross-connections or lower automation levels. However, the methodological nature of the approach allows for adaptation to other facilities given comparable data and models.

7 CONCLUSION

This paper addressed the critical problem of inaccurate energy performance characteristics in thermal power plants caused by the reliance on static regulatory documentation that fails to capture equipment degradation and operational drift.
We proposed a novel approach based on a self-adaptive digital twin that undergoes continuous intelligent updating using real-time monitoring data. The method involves constructing a physics- based model, its initial parameterization, and subsequent autonomous reparameterization via an algorithm that can perform anything from local adjustments to full model reconstruction based on data availability. This enables the accurate simulation of both standard and non-standard operating scenarios. Experimental evaluation on real industrial data demonstrated the high effectiveness of the approach: deviations in estimating the technological minimum were reduced from 17.4% to 0.7%, and deviations in fuel consumption calculation were reduced from 7.9% to 1%. These results confirm that the proposed self-adaptive digital twin framework significantly enhances the reliability and accuracy of energy modeling in TPPs, providing a solid foundation for autonomous, self-learning systems in the energy sector.

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