Designing a Smartfarm Energy Digital Twin Using Multi-Year Power Consumption

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Abstract— **This paper presents a preliminary methodology for designing an energy-centric digital twin for a smart-farm greenhouse using multi-year operational power data. Hourly main load is derived from device-level heating logs and evaluated across two winters (Jan–Mar 2023 for training and Jan–Mar 2024 for validation). A lightweight linear regression estimator using heating power signals and temporal features achieves stable cross-year performance (MAE 2.1 kW, RMSE 3.4 kW) and reproduces daily heating cycles and peak-load ramps. The results indicate that computationally efficient estimators can support early-stage digital twin integration and enable scenario-based energy assessment.**

Keywords— smartfarm energy management, digital twin , multi-year power analysis , lightweight energy modeling , linear regression

I. INTRODUCTION (HEADING 1)

Smartfarm systems have rapidly expanded worldwide as a core technology for improving agricultural productivity and automation[1]. Driven by the adoption of sensor networks, data-driven control, and energy-intensive environmental management, the global smart agriculture market has grown steadily, and ICT-based facility agriculture in Korea has increased from a marginal share of cultivated area to several thousand hectares of digitally managed greenhouses[2]. These facilities typically operate with a high degree of automation, enabling precise control of temperature, humidity, CO_2 concentration, irrigation, and ventilation[3].

However, this automation has also intensified energy use, particularly for heating and cooling during winter operation. Heating and cooling frequently account for 40–60% of total operating costs in commercial smartfarm greenhouses, and recent increases in electricity and fuel prices have further amplified the burden of winter energy bills[4-6]. In many cases, these energy costs offset the productivity gains achieved by smartfarm technologies, making climate-control energy one of the key constraints on the long-term economic sustainability of smartfarm operations.

To mitigate these challenges, numerous studies have analyzed greenhouse energy consumption using device-level power logs or single-season datasets[7]. Most existing approaches rely on conventional regression, correlation analysis, or short-term forecasting[8]. While these methods provide useful insights into seasonal trends and peak loads, they are limited in capturing the operational complexity of real farms, in generalizing across multiple winter seasons, and in supporting proactive decision-making. In particular, traditional data-driven analyses cannot reproduce realistic operating scenarios or evaluate hypothetical strategies—such as changing heating setpoints or modifying equipment schedules—before implementation.

Digital twin (DT) technology offers a promising way to address these limitations by virtually representing the physical environment, equipment, and energy behavior of smartfarms. DT-based systems can integrate real power records, simulate energy usage under alternative operating strategies, and assess the impact of environmental or seasonal changes in a risk-free virtual space[9]. Nevertheless, DT research in agriculture is still at an early stage, and energy-centric smartfarm digital twins that exploit multi-year operational data remain scarce.

In this study, we propose a preliminary design methodology for a smartfarm energy digital twin based on multi-year power consumption analysis. Using real device-level power logs collected over two consecutive winter seasons in a commercial greenhouse, we characterize energy usage patterns at the subsystem level and derive design requirements for an energy-focused digital twin capable of supporting future simulation-based decision making. Unlike prior work that relies on single-season datasets, our multi-year analysis captures inter-annual variations in heating demand and equipment operation, providing a more realistic foundation for DT configuration and validation.

The remainder of this paper is organized as follows. Section II reviews related work on smartfarm energy analysis and agricultural digital twins. Section III describes the smartfarm facility, the metering infrastructure, and the structure of the multi-year power logs. Section IV presents the proposed energy digital twin architecture and configuration. Section V introduces a lightweight preliminary energy model and evaluates its ability to reproduce multi-year consumption patterns. Finally, Section VI concludes the paper and discusses future research directions.

II. RELATED WORK

A. Power Consumption Characteristics and Analysis in Smartfarm

Energy use especially for heating and cooling is a dominant operational burden in modern smartfarms, often accounting for 40–60% of total costs[10-12]. Prior studies have analyzed device-level power patterns and environmental factors using statistical or machine-learning methods to predict short-term heating demand[13]. However, most analyses rely on single-season datasets, limiting their ability to capture inter-annual variability or generalize across different winter conditions. As a result, existing approaches offer only narrow temporal insights and provide limited support for long-term energy planning.

B. Digital Twin Applications in Agriculture and Smartfarm

DT technologies have been applied in agriculture for greenhouse monitoring, hydroponic control, and crop growth prediction, typically by integrating IoT data with simulation engines. Recent data-driven DTs enable predictive analytics and scenario evaluation, but most focus on environmental or crop modeling rather than energy behavior[14]. Furthermore, these DTs are generally built on single-period datasets, restricting their capability to evaluate seasonal changes or long-term operational trends.

C. Distinctions of This Study and Gaps in Existing Research

A clear gap remains between smartfarm energy analysis and DT research. Energy studies lack mechanisms for virtual scenario testing, while agricultural DTs seldom incorporate multi-year operational data needed for realistic energy modeling. This study addresses these limitations by designing an energy-oriented smartfarm DT based on two consecutive winter seasons of real power logs. The multi-year perspective enables identification of inter-annual differences in heating demand and subsystem operation, forming a robust foundation for future simulation-based energy strategy evaluation.

III. DATASET AND DATA COLLECTION

A. Smartfarm Overview

Figure 1. Panoramic view of the rental greenhouse at Goheung Smart Farm Innovation Valley.

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The dataset used in this study was collected from a commercial smart farm located in the Smart Farm Innovation Valley in Goheung, Jeollanam-do, as shown in Figure 1. This facility consists of a multi-span glass greenhouse with a total cultivation area of approximately 648 m², representing modern Korean smart farm facilities in terms of structural design and equipment configuration. The primary crop grown in the greenhouse is strawberries, a high-value horticultural crop requiring precise environmental and energy management during winter production [15].

The glasshouse is equipped with a typical set of energy-related systems, including multiple heat pump units for thermal conditioning, fan coil units (FCUs) for air distribution, circulation and nutrient solution pumps, horizontal screens for thermal insulation, and additional auxiliary equipment such as circulation fans and sulfur fumigation devices. These systems are integrated into a smartfarm control environment that monitors and records device-level electrical power usage as part of daily operation. Because winter strawberry cultivation demands continuous heating and careful climate management, the facility provides an appropriate real-world testbed for analyzing smartfarm energy consumption and for designing an energy-oriented digital twin.

B. Energy Monitoring and Metering Setup

The smartfarm is equipped with a device-level electrical metering system that records power consumption from major subsystems, including heating units, fan-coil units, pumps, and auxiliary devices. Dedicated meters installed at the main distribution panel transmit real-time load data to a centralized gateway, enabling synchronized multi-channel logging.

All measurements are collected at a one-minute interval, allowing observation of short-cycle behaviors such as heat pump activation and circulation pump cycles. The fully automated acquisition process operates continuously throughout the winter production period. All device-level measurements are integrated into a unified time-series database, producing a high-resolution dataset suitable for subsystem-level energy analysis and for configuring the proposed energy digital twin.

C. Power Log Structure and Preprocessing

The dataset is organized as time-stamped records at one-minute resolution from January to March, with each entry representing instantaneous device-level power measurements. Preprocessing includes checking for missing or duplicated timestamps and resampling the data to consistent intervals (e.g., one-minute or hourly) depending on analytic needs.

Device-level values can be analyzed individually to examine subsystem behavior or combined to compute composite indicators such as total heating demand and overall greenhouse power usage. These processed features form the primary inputs for the energy modeling and digital twin development in this study.

D. *Multi-Year Summary of Power Consumption*

A comparison of the 2023 and 2024 winter power logs reveals clear inter-annual variability in heating-related energy usage.

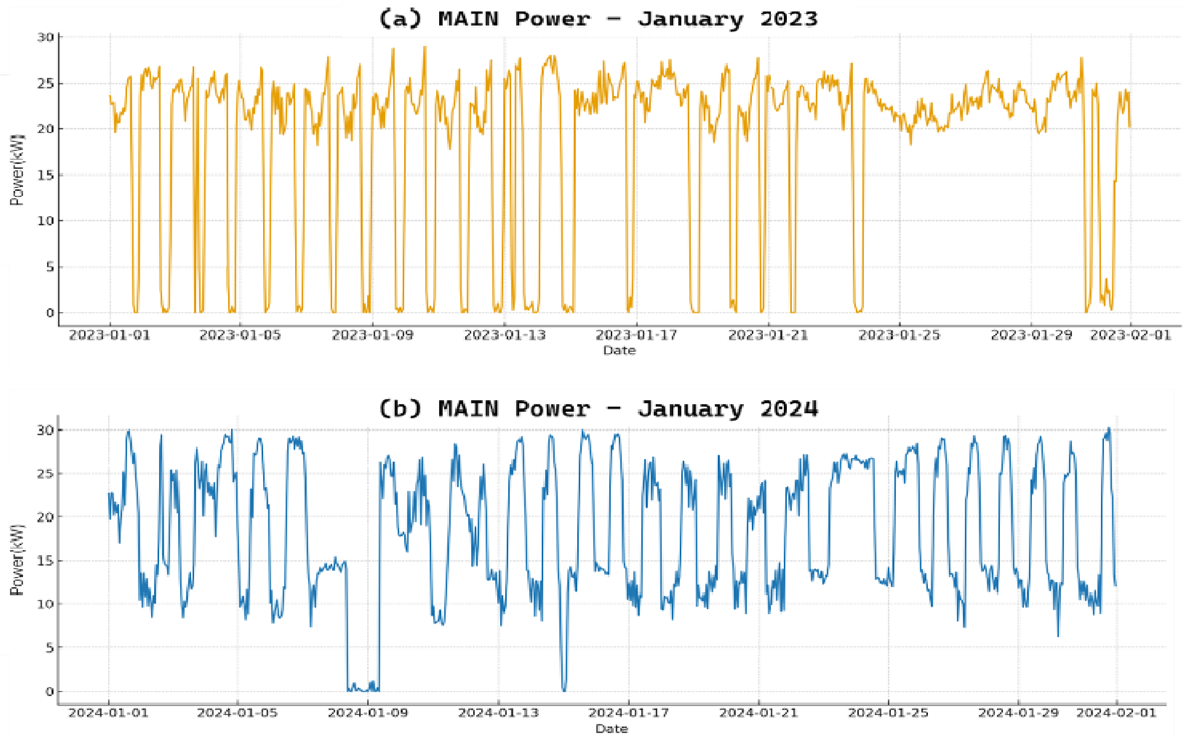

Figure 2. Hourly mains power profiles for January 2023 and 2024.

Figure 2(a) shows the main power profile for January 2023, where heating behavior follows a relatively stable pattern. Power levels remain concentrated around 23–27 kW during active periods, and the daily cycles exhibit consistent plateaus and predictable off-cycle intervals. This pattern indicates steady thermal requirements and a uniform heating schedule throughout the 2023 winter period.

In contrast, Figure 2(b) illustrates the January 2024 power profile, which displays substantially greater variability in both magnitude and temporal structure. The heating load fluctuates from near-zero to peak values approaching 30 kW, with more frequent short-cycle activations and sharper transitions between high and low states. These irregularities imply larger indoor–outdoor temperature offsets, greater intra-day temperature swings, or changes in heat retention efficiency during early 2024. Supporting subsystems such as fan-coil units and circulation pumps also show elevated baseline activity in 2024, suggesting more persistent air distribution and thermal mixing demands, while non-heating subsystems remain minor contributors in both years.

Despite identical facility conditions and cultivation settings, the two datasets demonstrate distinctly different temporal signatures: 2023 presents smooth and repetitive heating cycles, whereas 2024 exhibits more dynamic and volatile behavior. These findings underscore the inherent year-to-year uncertainty in smartfarm energy consumption and highlight the need for a digital-twin-based modeling framework capable of generalizing across multiple operational seasons rather than relying on a single-year dataset.

IV. Digital Twin Architecture and Design Requirements

A. *Digital Twin Concept and Design Principles*

The DT proposed in this study aims to provide a virtual representation of the smartfarm's energy behavior that mirrors the operational characteristics of the physical system. Unlike traditional simulation tools, which rely on predefined physical models or static assumptions, a DT continually integrates real operational logs to reflect the actual conditions of the system and support data-driven scenario evaluation. In the context of smartfarm heating operations where energy consumption is highly sensitive to seasonal variations, equipment aging, and daily operational strategies a DT must be designed to remain both lightweight and adaptable to changing real-world conditions.

To meet these objectives, the DT in this study adheres to the following design principles:

- Data-Centricity: The DT should utilize multi-year, device-level power logs as its primary information source, ensuring that the virtual model reflects real operational tendencies rather than idealized thermal responses.
- Modularity: Each component of the DT (physical mapping, data processing, energy modeling, and scenario simulation) should function independently,

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allowing modular refinement without altering the entire system.

- Generalizability: The DT should be capable of reproducing energy behavior across different operational years, capturing inter-annual variability in heating demand and equipment performance.

- Lightweight Implementation: To support practical deployment in commercial farms, the DT should rely on computationally efficient modeling techniques and avoid excessive dependence on complex physics-based simulations.

- Scenario Expandability: The DT must be prepared to evaluate what-if scenarios such as modifying heating setpoints, altering daily schedules, or optimizing device combinations to support decision-making in future work.

These principles form the foundation for the layered DT architecture described in the next section.

B. Layered Architecture of the Proposed Energy Digital

The proposed digital twin follows a four-layer architecture that mirrors the structure of typical DT implementations in industrial energy systems while being adapted specifically for smartfarm operations. Each layer performs a distinct role, and together they form an integrated pipeline from real-world measurement to virtual simulation.

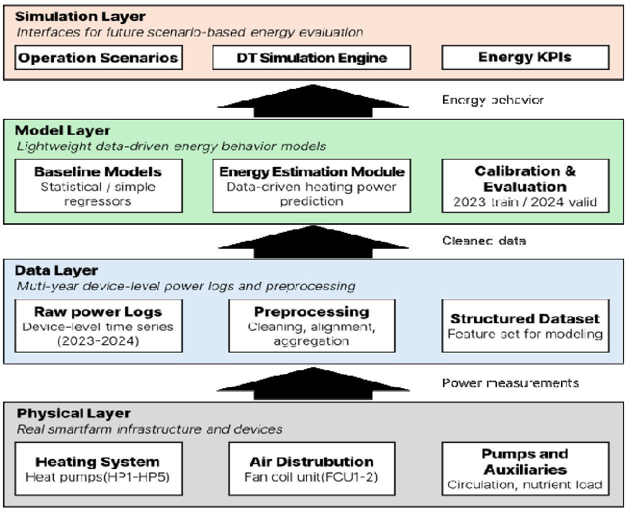

Figure 3. Overall architecture of the proposed smartfarm energy digital twin

Figure 3 presents the overall architecture of the proposed smartfarm energy digital twin. The DT is structured as a four-layer framework designed to translate raw device-level power measurements into a virtual representation capable of supporting future scenario-based energy analysis.

The Physical Layer models the real smartfarm infrastructure, including the heating system (HP1–HP5), air distribution units (FCU1–2), and pumps and auxiliary devices. Each component corresponds directly to an element in the virtual DT to ensure structural alignment between the physical and digital environments.

Above this, the Data Layer handles the acquisition, preprocessing, and structuring of multi-year power logs. Raw power measurements collected over the 2023–2024 winter seasons undergo cleaning, time alignment, and temporal aggregation to produce a structured dataset suitable for model calibration. This layer ensures data consistency and supports both historical and real-time integration.

The Model Layer contains the lightweight energy behavior models that form the core of the DT. It includes simple baseline models as well as the proposed energy estimation module, which performs data-driven prediction of heating-related power consumption. A calibration and evaluation block is used to validate generalizability by training on 2023 data and testing on 2024 data, reflecting the interannual variability observed in smartfarm operation.

At the top, the Simulation Layer provides interfaces for future scenario-based evaluation. Although full scenario experiments are beyond the scope of this preliminary work, the architecture defines the necessary structures for applying hypothetical operation strategies such as altered heating setpoints or modified equipment schedules through the DT simulation engine. The resulting outputs are expressed as energy KPIs that can inform decision-making in future studies.

C. Proposed Energy Digital Twin Configuration

Based on the identified design requirements, the proposed smartfarm energy digital twin consists of three core components: a structural mapping module, a lightweight energy estimation module, and a simulation interface. The structural mapping module defines the correspondence between real-world devices—such as heating systems, FCUs, and pumps—and their virtual representations. The energy estimation module leverages multi-year historical logs to approximate baseline consumption patterns and capture inter-annual variability using a computationally efficient model. Finally, the simulation interface establishes a logical framework for future scenario testing and strategy evaluation. Together, these components form a coherent preliminary digital twin that reflects real smartfarm energy behavior and provides a foundation for scenario-oriented energy optimization.

D. Implementation Workflow for Lightweight Energy Modeling

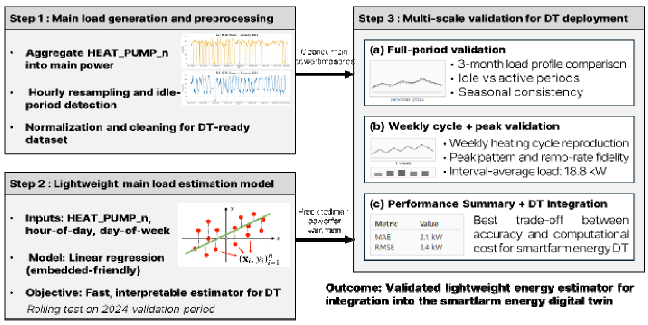

Figure 4. Overall workflow of the proposed smartfarm energy digital twin modeling process.

Figure 4 illustrates the implementation workflow used to construct the lightweight energy estimation module and prepare it for integration into the smartfarm energy digital twin. The workflow consists of three sequential stages: (1) main load generation and preprocessing, (2) lightweight model development, and (3) multi-scale validation for DT deployment.

In Step 1, device-level operation logs from the heating-oriented greenhouse are aggregated and resampled into hourly main load signals. Long-duration idle periods are automatically identified and removed, and the resulting time series undergoes cleaning, normalization, and alignment to form a DT-ready dataset suitable for multi-year analysis. This step ensures structural consistency and reduces noise that could hinder model generalization across operational seasons.

In Step 2, a computationally efficient and interpretable main-load estimator is developed using linear regression. The model incorporates Power consumption, hour-of-day, and day-of-week as input features, enabling embedded-friendly inference that aligns with the real-time constraints of digital-twin execution. The design intentionally avoids complex physics-based models, prioritizing fast computation, interpretability, and compatibility with limited computing resources typically available in commercial greenhouse systems.

In Step 3, the estimator undergoes multi-scale validation to assess its generalizability and suitability for DT deployment. Validation includes full-period comparison over a three-month winter horizon, weekly cycle consistency, and peak-load reproduction tests. The model demonstrates stable performance across both active and idle phases, achieving MAE of 2.1 kW and RMSE of 3.4 kW, while accurately capturing characteristic heating cycles observed in the greenhouse's operational data. These outcomes confirm that the proposed estimator provides a balanced trade-off between accuracy and computational efficiency.

Overall, the workflow presented in Figure 4 establishes a practical implementation pathway for integrating a lightweight, data-driven energy estimation module into the smartfarm energy digital twin. By relying on minimal sensor inputs and multi-year operational logs, the proposed approach satisfies the core requirements of generalizability, real-time adaptability, and scenario-expandable DT design.

V. Preliminary Modeling and Evaluation

A. Modeling Objective and Overview

The objective of the preliminary modeling is to evaluate whether a lightweight, data-driven energy estimation module can be embedded into the proposed digital twin. Rather than maximizing prediction accuracy, the goal is to verify that a simple model trained on real operation logs can reproduce the essential characteristics of multi-year power consumption. To support this objective, greenhouse-level main power is used as the target variable, and all device-level measurements are aggregated into hourly time series to reduce noise and align with operational timescales.

A year-to-year evaluation strategy is applied: January–March 2023 data are used for training, and the corresponding period in 2024 is reserved for validation. This setup examines whether a model fitted to one winter season can generalize to another with different weather conditions and operational states, thereby assessing its suitability for digital-twin integration.

B. Lightweight Linear Energy Estimation Model

To satisfy the real-time and interpretability requirements of the digital twin, a lightweight linear regression model is adopted as the primary estimator. The model predicts hourly main power consumption using aggregated subsystem loads—such as heat pumps, fan-coil units, circulation pumps, and auxiliary devices—together with temporal indicators like hour-of-day and day-of-week. This linear formulation provides transparent parameter interpretation and ensures computational efficiency suitable for real-time digital-twin deployment. Missing values after aggregation are imputed feature-wise to maintain a consistent input structure.

C. Evaluation Methodology

The evaluation examines whether the proposed lightweight model can reproduce smartfarm energy consumption patterns across different years. All device-level measurements are aggregated into hourly resolution to align with greenhouse energy planning practices. A year-to-year validation strategy is applied: the model is trained on January–March 2023 power logs and evaluated on the corresponding 2024 data. This configuration allows assessment of generalizability under changes in weather conditions, heating demand, and equipment operation.

Model performance is assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which quantify average deviations and peak-period discrepancies, respectively. This evaluation setup emphasizes cross-year reproducibility rather than strict prediction optimization, consistent with the digital twin's objective of capturing representative heating-cycle behavior.

D. Results

Figure 5 presents the evaluation results of the lightweight linear regression model using a combined visualization. Figure 5(a) shows the full-period comparison between the primary power profile and the model output for the 2024 heating season. The model was trained on 2023 data and evaluated on the unseen 2024 dataset using only power consumption signals and simple temporal features. Despite this minimal input configuration, the model reproduces the overall heating trajectory with high fidelity, achieving a MAE of 2.1 kW and an RMSE of 3.4 kW at an average load level of approximately 18.8 kW. The shaded region indicates a mid-February to mid-March idle period, during which both the actual power and predictions remain close to zero, confirming that the estimator does not generate spurious loads during non-heating phases.

Figure 5(b) provides a weekly zoom-in for the period from 1 to 8 February 2024 to examine short-term behavior. The predicted curve closely follows the main power across multiple day–night cycles, successfully capturing rapid morning ramp-ups, sustained peak plateaus, and shutdown transitions. Minor deviations are observed primarily around steep transitions, where abrupt load changes occur within one or two time steps; however, these errors remain sufficiently small for scenario-based energy evaluation within the digital twin framework.

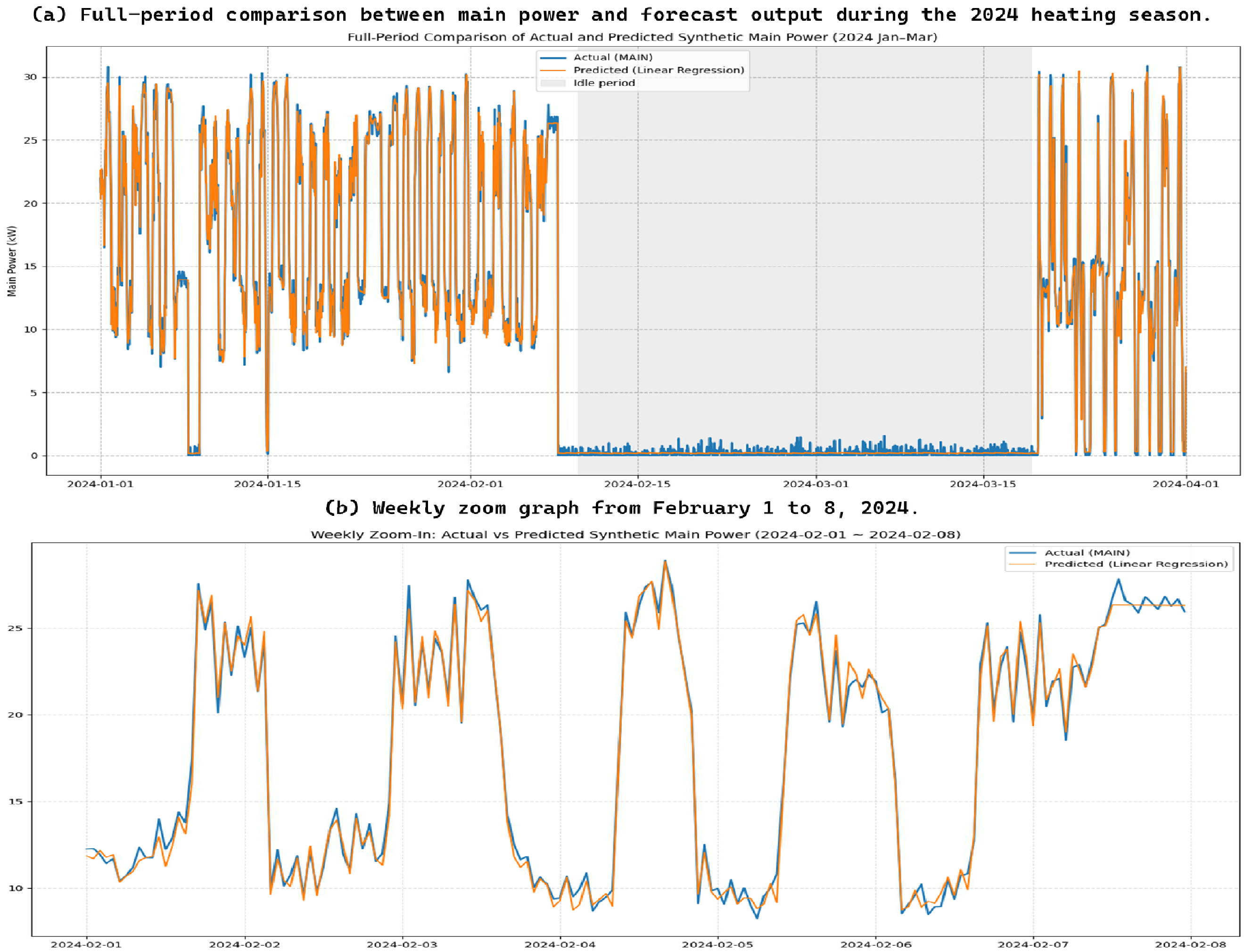

Figure 5. Performance evaluation of the lightweight linear energy estimator. (a) Full-period comparison between main power and predicted output for the 2024 heating season, with the shaded region indicating an idle period. (b) Weekly zoom-in from 1–8 February 2024, highlighting the reproduction of daily heating cycles and peak-load transitions.

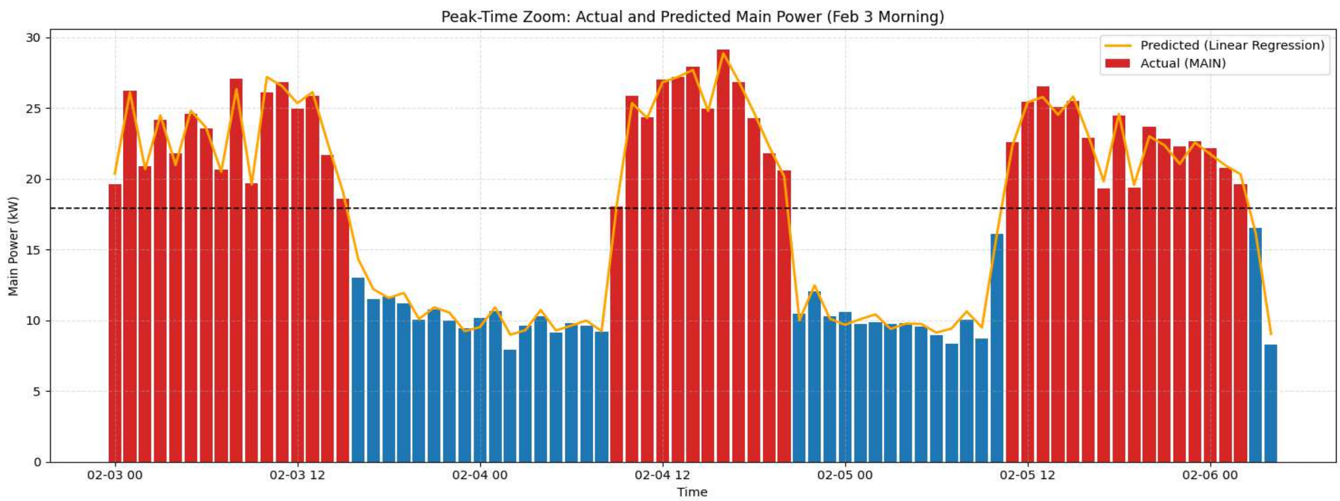

Figure 6. Peak-time zoom of the main power during February 3–6.

Figure 6 provides a high-resolution zoom-in of the period from February 3 to February 6, highlighting peak-load behavior. Actual main power is visualized using color-coded bars, where values above the average load of 18.8 kW are shown in red and lower-load periods in blue, enabling intuitive identification of heating-intensive hours. The lightweight linear regression model shows strong alignment with the actual load profile, particularly during peak ramp-up and ramp-down phases, closely tracking transitions between high- and low-demand states. Minor deviations appear mainly during abrupt peak fluctuations, which are expected given the simplicity of the model and the stochastic nature of the data.

Across all validation scales, the results confirm that the proposed estimator reliably captures the dominant characteristics of greenhouse heating demand. Full-period and weekly analyses demonstrate stable long-term performance and consistent reproduction of daily heating cycles, while the peak-time zoom verifies adequate fidelity in high-load morning periods. These findings indicate that, even with minimal inputs—two heat-pump signals and simple temporal features a computationally efficient model can provide sufficient accuracy for digital twin integration and scenario-based energy evaluation in practical smartfarm environments.

E. Discussion

The results confirm that a lightweight linear estimator is sufficient to reproduce the essential heating load behavior required for digital twin integration. Using only power consumption and simple temporal features, the model consistently captures seasonal variations, daily heating cycles, and peak demand patterns across two winter seasons. This indicates that high model complexity is unnecessary in the early DT phase and that a computationally efficient approach can provide reliable and generalizable performance. The cross-year analysis further emphasizes the importance of multi-year validation for DT robustness under varying operating conditions. Overall, the findings demonstrate that a simple and interpretable model offers a solid foundation for the initial energy module of a smartfarm digital twin.

VI. CONCLUSION

This study proposed a lightweight energy estimation framework for integration into a smart farm energy digital twin. Using power consumption data, key loads were generated, preprocessed, and validated across multiple temporal scales. A linear regression model was adopted as the core estimator due to its interpretability, computational efficiency, and suitability for embedded execution. Despite its simplicity, the model successfully reproduced essential heating-related patterns, including diurnal cycles, seasonal variations, and peak-load behavior, demonstrating its effectiveness as a digital twin component. The results confirm that a computationally efficient approach can provide an appropriate balance between prediction accuracy and integration cost for real-time DT deployment in greenhouse environments.

Future work will focus on incorporating environmental variables to improve load realism, extending the framework to support multi-device and multi-zone configurations, and integrating the estimator into a closed-loop DT architecture for scenario-based optimization, adaptive control, and anomaly detection.

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