Digital Twin–Enabled Data-Driven Strategy for Real-Time Thermal Control in Direct Hybrid Solar Dryers

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Abstract. In this study, a high-fidelity digital twin structure for the adaptive thermal regulation of hybrid direct solar dryer is proposed. Matlab's System Identification Toolbox was used to identify the dynamic models of the drying chamber temperature and humidity from experimental data. An Extended Kalman Filter (EKF) was used for real-time state estimation and online updating of the model parameters during varying operating conditions to maintain an accurate real-time synchronization between the physical system and its virtual counterpart. This updated digital twin was subsequently used within a predictive functional control (PFC) strategy permitting better disturbance rejection and compensation for the sluggish thermal dynamics of the drying process. Moreover, a Hybrid Adaptive Differential Evolution (HADE) algorithm was implemented for adaptive tuning of the control and model parameters, enhancing robustness and tracking performance in a nonlinear environment. The physical dryer (controlled by a National Instruments PLC) was physically connected to the virtual model, which had been developed in MATLAB and interfaced through LabVIEW using a bidirectional TCP/ IP communication architecture. These enable reliable monitoring, adaptive thermal regulation, and real-time accurate prediction per experimental results.

1 Introduction

The rising global demand for energy-efficient and sustainable technologies for food preservation has accelerated research into advanced drying systems. Out of these, hybrid solar dryers have been proven to be a potential solution considering their capability to combine renewable solar energy with non-renewable auxiliary sources of low-grade thermal energy together for most suitable reliable drying quality by effectively utilizing comfortable climatic conditions [1]. Nevertheless, even if favourable, there are still issues such as thermal regulation aspects, energy efficiency and product quality preservation related with these hybrid solar dryers. Mainly, these challenges are due to strong coupling among the three

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partial differential equations governing the highly nonlinear and time-varying heat- and mass-transfer processes taking place within the drying chamber [2].

Due to this complexity a typical resolution pattern implemented by traditional heuristic control like proportional–integral–derivative (PID) controller or empirical tuning methods, ultimately fails to ensure the optimal performance in such environments. These limitations becomes discernible with varying solar irradiance and ambient conditions, poor tracking of temperature, inefficient utilization of thermal energy and variation in quality of drying [3]. In order to get around such constraints, the robotic current control approaches based on data-driven modeling and optimization techniques have been studied recently. Especially, metaheuristic optimization algorithms possess distinguished capability of providing solutions for nonlinear, multimodal and multi-objective problems [4], which makes it a highly suitable candidate to tune controller designs in dynamic thermal systems.

Concurrently, digital twin–the recently evolving term of great interest to thermal process engineering and smart manufacturing. Digital Twin is generally see as a dynamic virtual representation of physical system or process that brings together real-time data collection, physics-based models and data-driven methods to monitoring, prediction, and control [5]. Digital twins have shown promise in thermal food processing applications to model and support complex heat transfer dynamics and advance control strategies predictive or adaptive control schemes [6]. Recent advances reinforce the combination between reduced-order models and neural ordinary differential equations that improve computational performance while maintaining solutions that are accurate enough for real-time implementation [7].

The major challenge while implementation of digital twin is the real time data synchronization between physical and virtual system. To overcome this issue, state estimation approaches have been used more for robotics applications such as Extended Kalman Filter (EKF). The Extended Kalman Filter (EKF) [8], as a recursive estimator, is capable of utilizing new measurements to update model states and parameters in real-time, while the model fidelity and robustness against uncertainties/disturbances are both improved. This is especially helpful for hybrid solar dryers where system response is largely driven by environmental variation and system nonlinearities.

Furthermore, the fusion of digital twin technology with data-driven optimization and artificial intelligence paves the way for new paradigms in intelligent thermal control. Digital twins can use real-time data to continuously update model parameters, which allows them to capture system dynamics much more accurately and improve control performance. It is in this context that optimization algorithms like Hybrid Adaptive Differential Evolution (HADE) are needed to efficiently tune model and controller parameters to offer optimal performance during variable operating conditions. More recently, adaptive estimation techniques combined with advanced optimization strategies were also required in mitigating the complex trade−off to improve system reliability and energy efficiency of large-scale energy systems.

However, it remains in an infant stage with respect to real-time thermal control based on digital twin framework. Most of the existing works are limited to either system modeling or control design and they do not take advantage of real-time state estimation for intelligent optimization methods [9].

To address these gaps, this study proposes a novel digital twin–enabled data-driven framework for adaptive thermal regulation in hybrid solar dryers. The proposed approach combines an Extended Kalman Filter (EKF) [10] for real-time model calibration and state estimation with a Hybrid Adaptive Differential Evolution (HADE) algorithm for optimal parameter tuning. The EKF provides model state and parameter updates during the operation phase using real-time observations to accurately model the physical system, while the HADE algorithm allows for efficient search of optimal control parameters in a nonlinear time-varying environment. This hybrid method combines both model precision and control performance, providing an approach for better thermal regulation and increasing energy efficiency.

The main contributions of this work can be summarized as follows:

i. The development of a digital twin framework dedicated to thermal regulation in hybrid solar drying systems.
ii. The integration of real-time data acquisition and Extended Kalman Filter (EKF) for dynamic model updating and state estimation.
iii. The implementation of a Hybrid Adaptive Differential Evolution (HADE) algorithm for robust and adaptive parameter tuning.
iv. The validation of the proposed framework through simulation and experimental scenarios.

2 Digital Twin Architecture

2.1 Direct hybrid dryer description

For this research, the Direct Hybrid Dryer (DHD) uses a closed-structure design that integrates solar and electric heating for improved drying conditions. The system is built with a metal frame which offers structural support for outdoor solar drying. Glass panes mounted to the front and sides are designed for passive solar radiation entrance and temperature elevation via the greenhouse effect. Measuring 2.0 m x 2.0 m, DHD provides sufficient internal space for adequate heat retention and uniform air circulation. To minimize the DHD's reliance on solar ambient conditions, an auxiliary electric heater is used to improve low solar condition performance during active drying and to control temperatures. The DHD can decrease the drying process's dependence on solar irradiation, improve drying temperature control, and provide reliable uniform drying because of the combination of these design features.

2.2 Hardware system

The Direct Hybrid Dryer and Physical Domain System proposed (see Figure 1) integrates pure hardware components forming the operational basis for the along system. The Physical Domain combines sensing, actuation, and local control components, thus capturing and transacting process data for every operational tier. This architecture enables real-time control, monitoring, and closed-loop control systems, linking the physical and data layers of the digital twin. Measurement and actuation devices have been integrated into the system to ensure retention of the optimum drying conditions. An operational electrical heater (2kW) with fine temperature control augments the thermal energy during periods of scarcity of solar energy. The fan (Orion 12HB VXC) with a flow rate of 0.107 m^3/s assists in the uniform distribution of heat. The internal and external atmospheres are monitored concurrently by the HM-110 and TM-110, which are temperature and relative humidity sensors, respectively. The Kipp & Zonen pyranometer, which gauges solar radiation, gives an indication of solar energy present. The NI cRIO-9030 programmable logic controller handles data acquisition, control, and processing. This device implements the control algorithms, manages the sensor measurement processes, and operates the heaters and ventilators, providing guaranteed circuit behavior and prompt reaction of the system.

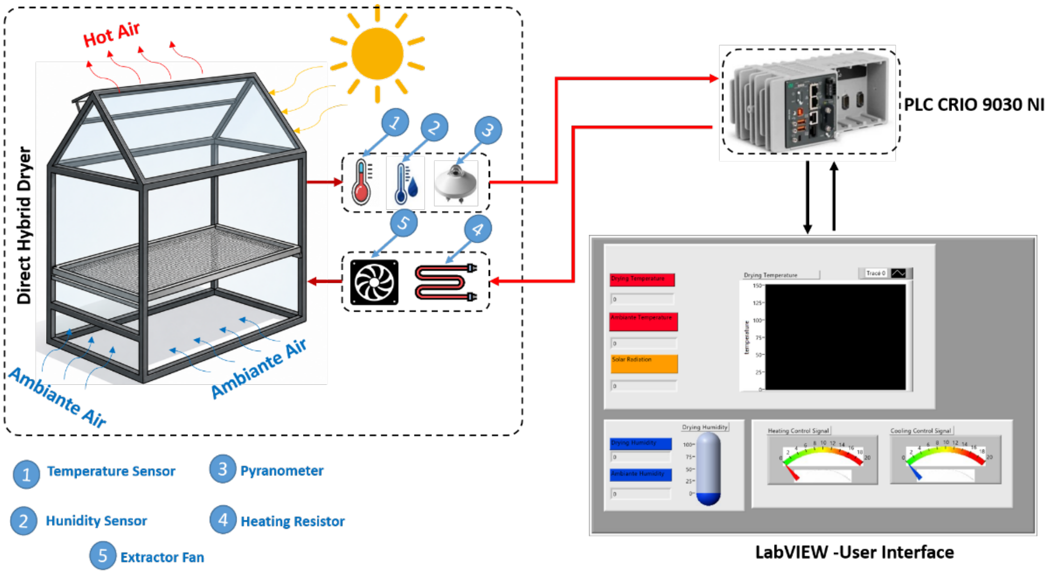

Fig. 1.Hardware system architecture

2.3 Cyber system

The cyber domain constitutes the computational layer of the Digital Twin [9], where system modeling, control algorithms, and real-time data processing are implemented (Figure 2). Using MATLAB/Simulink, a dynamic model that replicates the DHD's thermal and moisture characteristics has been developed. This model allows for effective simulation, prediction, and control of the drying process. This model facilitates the simulation, prediction, and controlling of the drying process. The physical layer and the virtual layer communicate in real time, bidirectionally, and through TCP/IP. As the PLC functions, the sensor data is relayed to the virtual model and thus, real time data synchronization is achieved. In this scenario, the cyber domain sent control commands to the PLC, which then adjusted temperature and ventilation, accomplishing closed-loop control. This significantly enhanced system performance. For the most part, the bidirectional data exchange fulfills the requirements of the system in terms of streaming, updating, and control:

- **Real-time data streaming:** Instantaneous transfer of temperature, humidity, and irradiance data from the physical domain to the cyber model.
- **Dynamic model updating:** The Simulink-based model continuously adjusts its internal states based on the measured operating conditions.
- **Intelligent decision-making:** Control algorithms executed in the cyber layer compute optimized commands that are relayed to the physical actuators.
- **Synchronized operation:** The TCP/IP layer ensures strict temporal synchronization between the physical and cyber domains, enabling real-time monitoring and closed-loop control. Overall, the cyber domain acts as the computational intelligence of the Digital Twin, providing the predictive capability, decision-making tools, and simulation environment required to achieve advanced thermal control and improve the operational performance of the hybrid solar dryer.

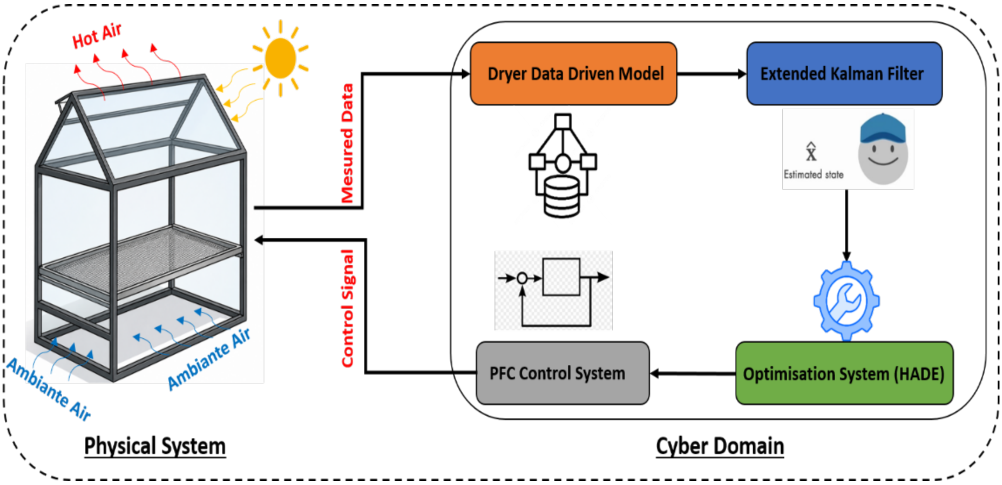

Fig. 2. Digital twin architecture: integration of physical and cyber domains

3 System modelling and control strategies

3.1 Digital Twin modelling system

The development of the digital representation solely relies on a mathematical modeling framework that describes the thermal and moisture flow dynamics of the dryer via direct and hybrid modeling approaches. For this part, the system identification techniques implemented in MATLAB were used to obtain time-variant models based on the experimental input-output measured data (Figure 3). This approach allows the digital model to remain consistent with the system's behavior and the operating conditions. The overall model of the dryer consists of three subsystems, each representing a different source of thermal and airflow.

- **Solar Subsystem Model**: This model describes the response of the dryer when the system receives only solar radiation, without the use of the auxiliary heater or the axial fan. The model captures the naturally occurring heating effect induced by solar radiation and illustrates the resulting variation in moisture within the system.
- **Electrical Heating Subsystem Model:** This model describes the thermal dynamics that involve using the electrical resistance heater. It measures the effect that auxiliary electrical heating produces on the internal air temperature and examines the impact on moisture reduction that occurs during the drying process.
- **Air Extraction Subsystem Model:** This model represents the effects that mechanically induced airflow from the ventilation system produces.

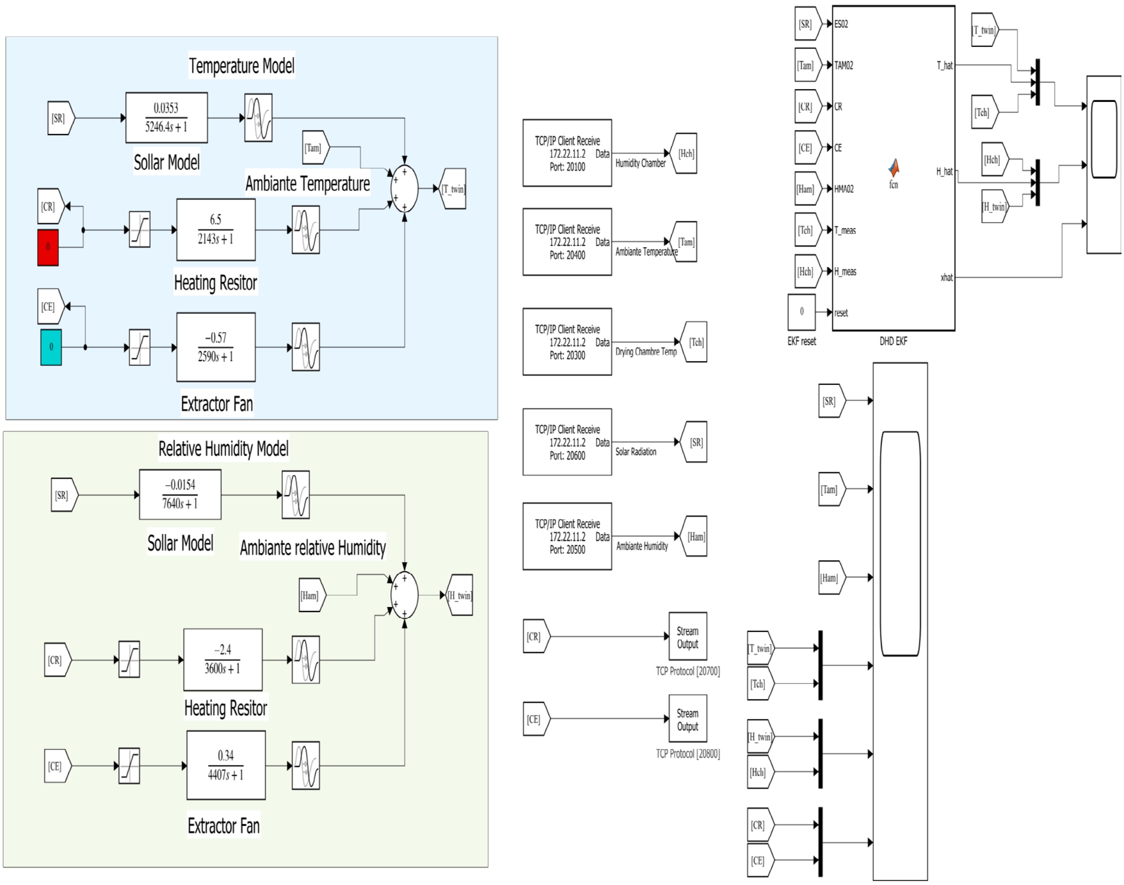

Fig. 3. Overview of the DT modeling system

3.2 Extended Kalman Filter-based state estimation model

An Extended Kalman Filter (EKF) [11] was implemented for online estimation of outlet air temperature and humidity in order to achieve accurate real-time synchronization between the physical dryer and its digital twin architecture. The model presented is a dynamic representation of the effect of solar irradiation, electrical heating and air extraction on the thermal and hygrometric behavior of the drying chamber.

The state vector was defined as:

$$x_k = [x_{T,S} \quad x_{T,R} \quad x_{T,E} \quad x_{H,S} \quad x_{H,R} \quad x_{H,E} \quad b_H]^T \tag{1}$$

Where $x_{T,S}$, $x_{T,R}$, $x_{T,E}$, represent the temperature contributions of solar radiation, heater, and extractor, respectively, while $x_{H,S}$,$x_{H,R,}$ and $x_{H,E}$, denote their corresponding effects on humidity.

The input vector is expressed as:

$$u_k = [S_k \quad T_{amb,k} \quad C_{R,k} \quad C_{E,k} \quad H_{amb,k}]^T \tag{2}$$

Where S_k is the solar irradiance, $T_{amb,k}$ the ambient temperature, $C_{R,k}$ the heater control signal, $C_{E,k}$ the extractor command, and $H_{amb,k}$ the ambient humidity.

A first-order transfer function with time delay was modeled for each thermal and hygrometric contribution:

$$G_i(s) = \frac{K_i}{\tau_i s + 1} \tag{3}$$

Where K_i is the static gain and τ_i is the time constant associated with the considered subsystem. After discretization with a sampling period Ts=60s, the state evolution equation becomes:

$$x_{i,k+1} = a_i x_{i,k} + b_i u_{i,k-d_i} \tag{4}$$

With:

$$a_i = e^{-T_s/\tau_i} \tag{5}$$

$$b_i = K_i(1 - a_i) \tag{6}$$

Where d_i denotes the discrete input delay.

The overall system dynamics were represented in discrete state-space form as:

$$x_{k+1} = Ax_k + Bu_{d,k} + w_k \tag{7}$$

Where A and B are the state and input matrices, respectively, $u_{d,k}$ is the delayed input vector, and w_k represents the process noise.

The estimated outlet temperature and humidity are reconstructed through:

$$\hat{T}_{out,k} = T_{amb,k} + x_{T,S,k} + x_{T,R,k} + x_{T,E,k} \tag{8}$$

$$\hat{H}_{out,k} = H_{amb,k} + x_{H,S,k} + x_{H,R,k} + x_{H,E,k} + b_{H,k} \tag{9}$$

Which can be written in compact form as:

$$\hat{y}_k = Cx_k + \begin{bmatrix} T_{amb,k} \\ H_{amb,k} \end{bmatrix} \tag{10}$$

Where $\hat{y}_k$ is the estimated output vector and C is the observation matrix.

EKF uses a recursive process of prediction and correction Steps proceeds as below:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_{d,k} \tag{11}$$

$$K_k = P_{k|k-1}C^T(CP_{k|k-1}C^T + R)^{-1} \tag{12}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - \hat{y}_{k|k-1}) \tag{13}$$

Where K_k is the Kalman gain, *P* the covariance matrix, *Q* the process noise covariance matrix, and R the measurement noise covariance matrix. The main contribution of the proposed EKF-based estimation strategy is to establish enhanced accuracy, robustness, and fast adaptability for the digital twin in terms of reliable state estimations and stable thermal process representation under variable operating conditions.

3.3 PFC control system architecture

In a climate condition with the higher requirements for environment sustainability, a Predictive Functional Control (PFC) strategy [12] is corroborated into the digital twin framework to control temperature level as well as coordinate controls in between electrical home heating resistor as well as air extraction system of hybrid solar–electrical dryer. Due to its low complexity and prediction feature, the PFC scheme is a fit for thermal systems with slow dynamics, coupled inputs, and external disturbances. It uses simplified first order internal models to predict the future thermal behavior of the drying chamber and determine control action over a finite prediction horizon with actuator constraints.

The formulation of the internal prediction model, set for each actuator, was represented by a discrete-time first-order representation:

$$y_m(k) = -a_m y_m(k-1) + K_m(1 + a_m)u(k-1) \tag{14}$$

Where $y_m(k)$ denotes the model output, u(k) the control input, a_m the discrete model parameter, and K_m the steady-state gain.

Assuming a constant manipulated variable over the prediction horizon, the predicted output sequence was analytically computed to reduce online computational effort.

We employed a decentralized control architecture using two separated SISO-PFC loops, one for the electrical heater and another in charge of the extractor system. We defined the tracking error in the future by:

$$e(k + i \mid k) = r(k + i) - \hat{y}(k + i \mid k) \tag{15}$$

Where $r(k + i)$ represents the target trajectory and $\hat{y}(k + i \mid k)$ the predicted process output

To achieve an appropriate thermal stabilization and to avoid sudden actuator changes, the reference trajectory that was generated is given according to:

$$T_{ref}(k + i) = T_{ref}(k) - \lambda^i\left[T_{ref}(k) - T_{ch}(k)\right] \tag{16}$$

Where λ∈ (0, 1) is the trajectory-tuning factor, which indicates how fast the algorithm converges. The PFC control law was formulated as follows based on the expected response and desired reference evolution:

$$u(k) = k_0(y_r - y(k)) + k_1 y_m(k) \tag{17}$$

Where y_r is the reference trajectory, $y(k)$ the measured output, and k_0, k_1 the predictive control gains. The proposed predictive framework allows for consistent and adaptive thermal regulation across dynamically changing climates while retaining its real-time implementability in the digital-twin setting.

4 Digital Twin Optimization Framework

In order to improve the thermal regulation performance of the proposed digital twin architecture, an optimal tuning of Predictive functional control (PFC) parameters was conducted by implementing a Hybrid adaptive differential evolution (HADE) algorithm. Specifically, the optimal prediction horizon np and trajectory tuning factor λ determined the dynamic response, stability, and robustness of the drying system to environmental perturbations, we solely optimized these two parameters during the study.

HADE was chosen, as it is capable of effectively solving nonlinear and multi-objective optimization problems while maintaining a good exploration-exploitation balance. Within this system, the optimization occurs in the digital twin environment where the virtual model of the dryer can simulate its thermal behavior as it adapts to different operating scenarios.

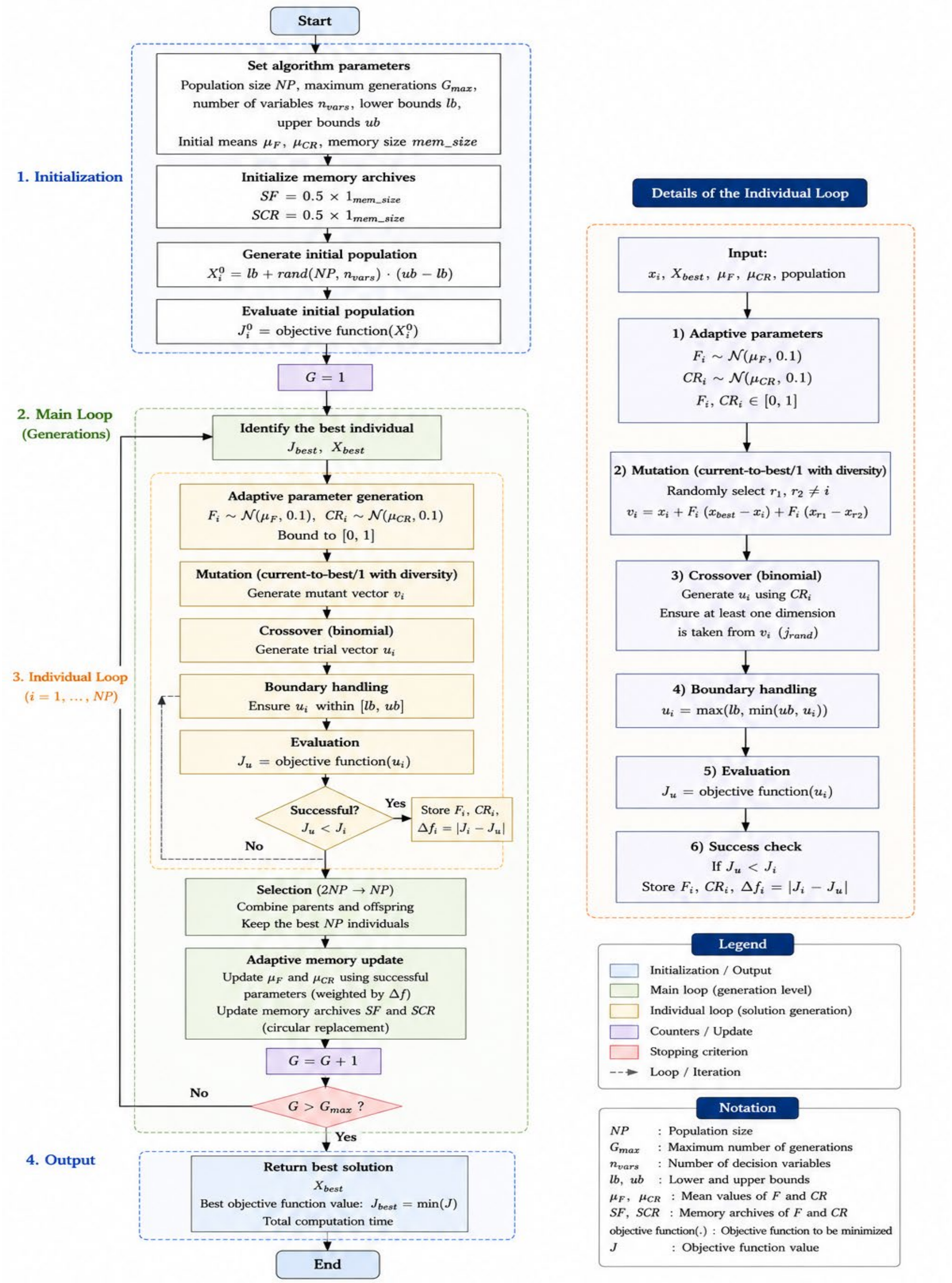

Fig. 4. Hybrid Adaptive Differential Evolution Algorithm flowchart

This interaction allows for ongoing feedback regarding performance, which can in turn be used to adaptively update the controller parameters.

The optimization objective considers a multi-criteria cost function comprising temperature tracking error, transient response performance and control effort smoothness. The chosen objective function has the form:

$$J = w_1 \sum_{k=0}^{N} |e(k)| + w_2 \sum_{k=0}^{N} k|e(k)| + w_3 \sum_{k=0}^{N} (\Delta u(k))^2 \tag{18}$$

Where:

- $e(k) = T_{\text{ref}} - T_{ch}(k)$ is the temperature tracking error
- $\Delta u(k) = u(k) - u(k-1)$ penalizes aggressive control variations
- w_1, w_2, w_3 are weighting coefficients

Among the objectives, the first term corresponds to Integral of Absolute Error (IAE), which ensures precise tracking. The second term corresponds to Integral of Time-weighted Absolute Error (ITAE) to favor quicker settling and ensure minimal steady-state deviation. The control effort is excessive in the third term, which is aimed at avoiding unnecessary stresses and switching of the actuators.

The flowchart of the proposed HADE-based optimization framework is illustrated in Figure 4.

5 Results and discussion

5.1 DT prediction error

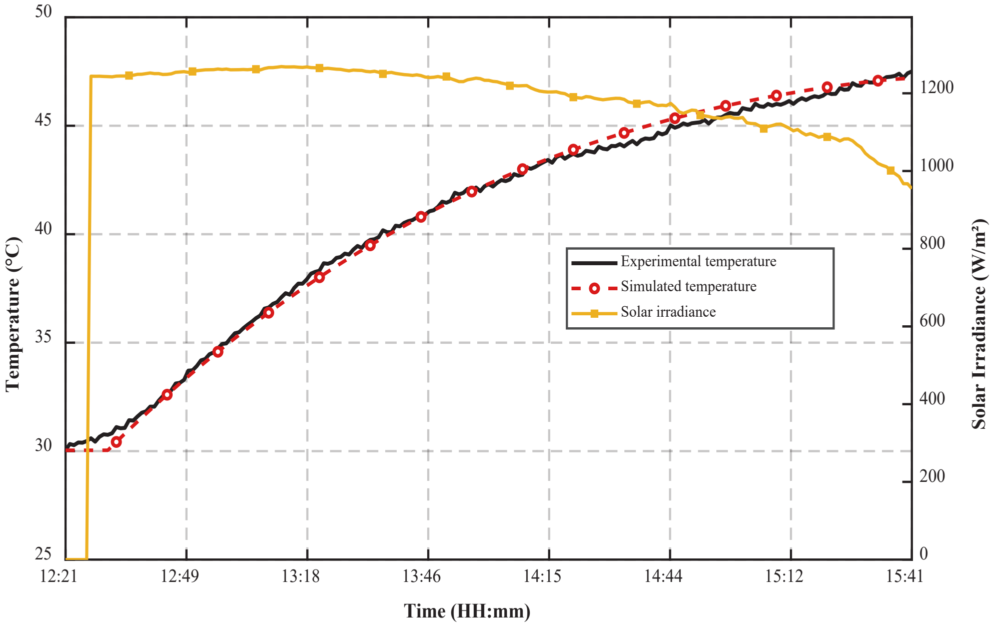

Fig. 5. Experimental Validation of the Digital Twin Temperature Response during Daytime Operation

In order to assess the prediction capacity and robustness of the proposed digital twin, two experimental cases were performed under different operating conditions. This was accomplished to demonstrate the capability of EKF-updated digital twin to recreate the thermal and hygrometric behavior of hybrid dryer in both renewable and auxiliary heating process.

The first test was conducted under daytime operation, to measure the effect of solar irradiation on model prediction accuracy. Here, the drying process was largely driven by solar energy which provided a platform to evaluate the digital twin interacting with climatic conditions that vary naturally. The chamber temperature predicted was compared with the experimental measurement, where an RMSE of 0.32 °C and a VAF value of 99.62% were achieved (Figure 5). Likewise, the results for humidity prediction shown in Figure 6 are associated with very well estimation accuracy which produced an RMSE of 0.26 % and a VAF of 99.80%. These results further highlight the capacity of the proposed estimation framework to capture the nonlinear thermal dynamics resulting from solar irradiance variations.

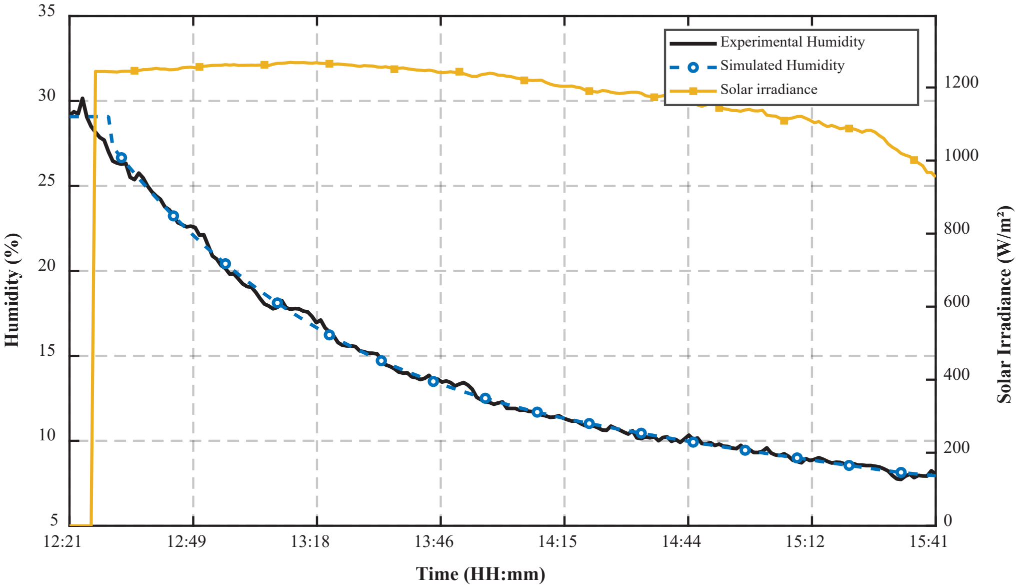

Fig. 6. Experimental Validation of the Digital Twin Humidity Response during Daytime Operation

Another experimental method was performed to evaluate the influence of applied electrical heating resistor on a suitable prediction fidelity of the digital twin. The experimental and predicted responses for temperature and humidity are shown in Figures 7 and 8, respectively. The temperature prediction results shown in Figure 7 yielded a root mean square error (RMSE) of 0.42 °C and a variance accounted for (VAF) value of 99.90%, indicating the proposed model was able to accurately follow the thermal behavior induced by the electrical heating system. In the same way, the humidity estimation results shown in Figure 8 confirmed the robustness and reliability of an EKF-based digital twin applied to actuator-driven thermal variations with RMSE as low as 0.32% and VAF index equal to 99.96%.

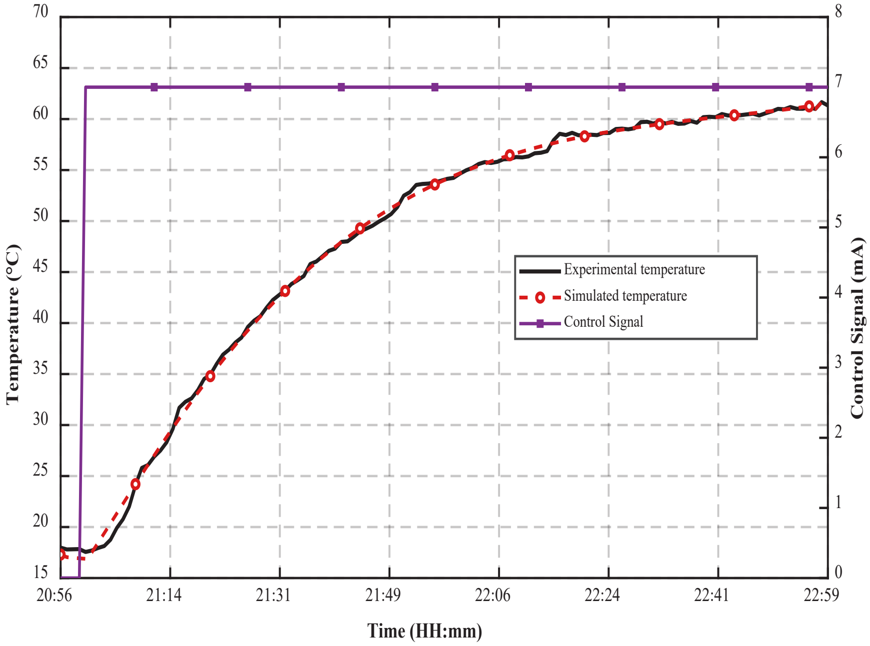

Fig. 7. Nighttime Experimental Validation of the Digital Twin Thermal Response

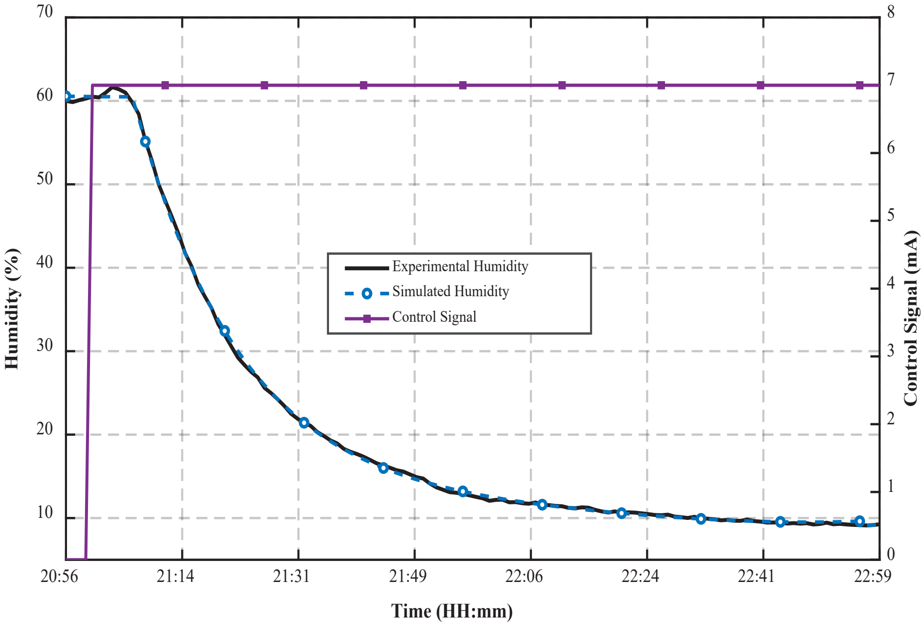

Fig. 8. Nighttime Experimental Validation of the Digital Twin Humidity Response

In conclusion, the results obtained show that the proposed digital twin recognizes highly accurate real-time temperature and humidity indicators under different operating modes. The low values of RMSE and high values of VAF indexes validate the ability of the developed framework to guarantee a robust thermal process representation against environmental disturbances and non-linear system behavior.

5.2 Performance Evaluation of the Optimization Framework

Figure 9 shows the convergence plot of the proposed Hybrid Adaptive Differential Evolution (HADE) algorithm, where the optimization process is conducted using 30 populations in each generation for a total of 30 generations. The resultant convergence profile exhibit steady and gradually declining behavior of the objective function, signifying the demonstrated effectiveness of our proposed strategy demonstrating the optimal parameters of the PFC controller.

The objective function values remain relatively high at the start of the optimization process, which is indicative of the HADE algorithm exploring its search space. When we look at the generations, a large drop of the objective function occurs indicating that as it goes deeper, it moves from global exploration to local exploitation. The convergence curve then converges near the optimum solution, also highlighting that the optimization framework in question is robust and numerically stable, being efficient to converge.

The optimization process indicated that prediction horizon of the best controller was np=30 and trajectory tuning factor λ=0.98. This configuration represented a good balance between acceleration robustness, control-response smoothness and track-following accuracy. The results thus obtained validate the ability of proposed HADE based framework in effectively tuning of PFC controller over a wide range operating under uncertainty.

In the following section, we describe the resulting thermal regulation performance and control behavior obtained by applying an optimized set of parameters to our controllers.

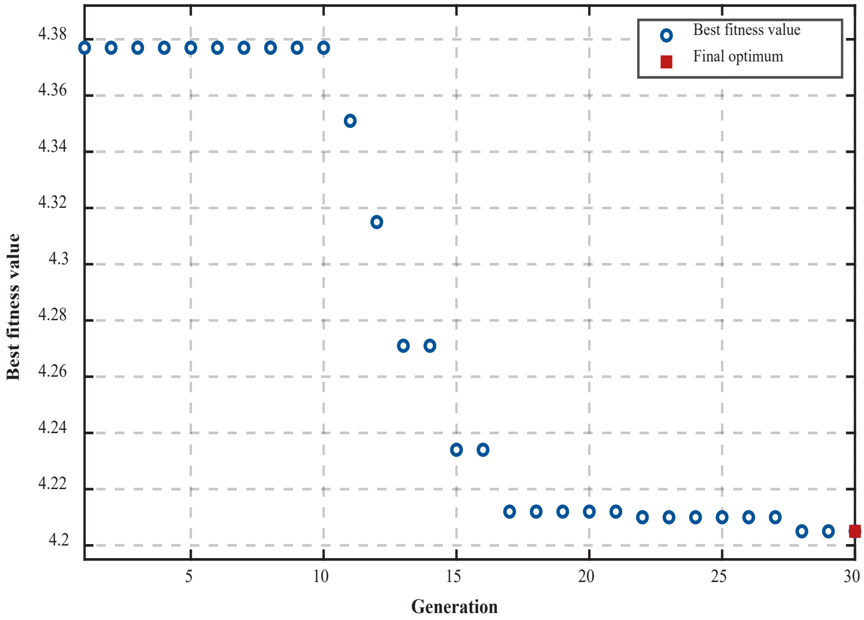

Fig. 9. Convergence Profile of the Proposed HADE Algorithm

5.3 Evaluation of the control system

After obtaining the optimization results elaborated in the previous section, Figure 10 shows the thermal control performance of DHD system with optimized PFC parameters by using HADE algorithm. A comparison of the PFC strategy with a conventional Proportional–Integral (PI) controller behavior is performed for temperature setpoints of 50 °C and 55 °C under four operating scenarios.

Cases 1 and 2 assess the system response when disturbed with no external meteorological disturbance under controlled operating conditions, while an artificial disturbance is introduced to evaluate the dynamic response of both controllers. The improved PFC strategy achieves better performance in terms of faster tracking response to the temperature reference signal, disturbance rejection capability as well as a small overshoot. Upon applying the same disturbance, by contrast, the PI controller settles more slowly with larger overshoot than is an indication of lower robustness and little predictive capability.

Then, cases from 3 to 4 are presented to analyze the controller performance with real operating ambient condition scenarios in the case of ambient temperature range between 15 °C–20 °C and solar irradiance level of 605 W/m² to 1200 W/m². Under these non-linear operating conditions, the proposed optimized PFC controller achieves simultaneous stability and low oscillations, as well as almost zero steady-state error of the thermal regulation. For comparison purposes, the control through the PI-based strategy has higher variability and is still disrupted externally than that based on simple output feedback with rotary parts. The obtained results clearly indicates that the developed HADE tuned PFC strategy is more superior to the conventional PI controller for thermal control of hybrid solar drying systems. Leveraging predictive control in the Digital Twin framework, the proposed methodology improves flexibility, disturbance rejection and thermal performance robustness to wide variations in environmental conditions.

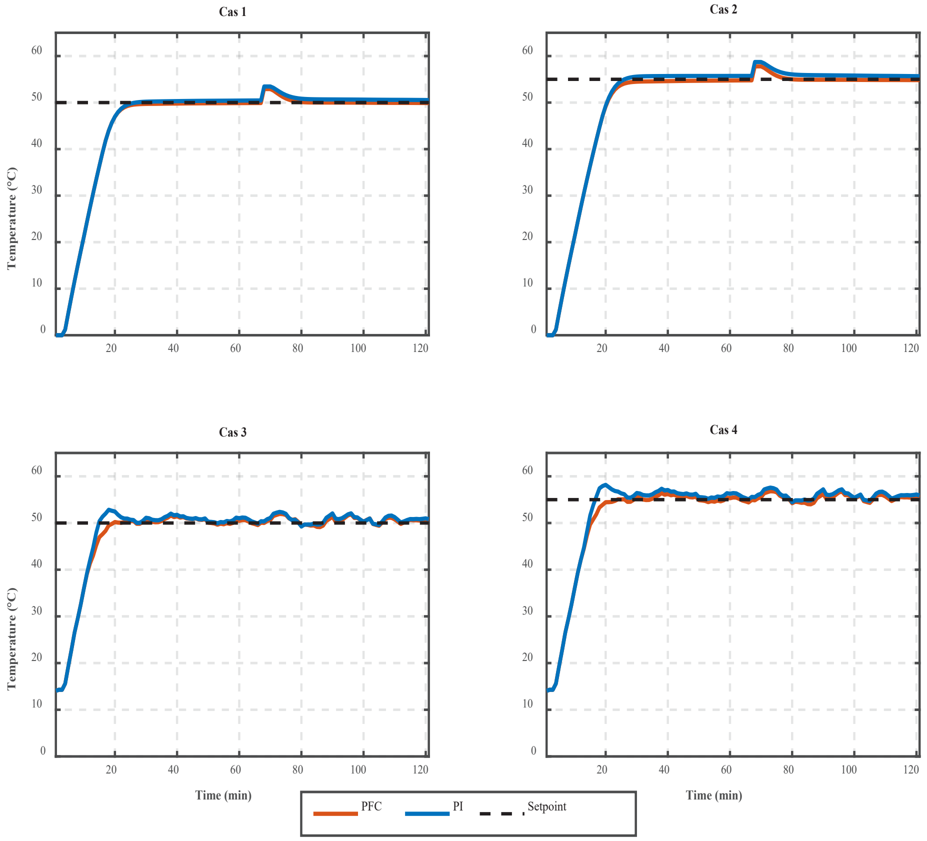

Fig. 10. Performance of DT–based temperature regulation at setpoints of 50 °C and 55 °C

6 Conclusion

The digital twin framework proposed in this study aimed to following real-time thermal managements of a hybrid solar–electrical dryer. The architecture combines data-driven dynamic modeling, real-time communication, adaptive state estimation, predictive control and intelligent optimization to enhance the monitoring and control performance of the drying process in varying climatic and operational conditions.

Experimental identification of thermal and hygrometric dynamics of the drying chamber using MATLAB System Identification Toolbox, incorporated in real time digital twin environment. Significant operational points of the physical system were estimated using an EKF-based estimation strategy to realize adaptive correction of the temperature and humidity states so that we compensate for disturbances, sensor noise, and parametric uncertainties. Also, a TCP/IP communication architecture has been built up among National Instruments PLC, LabVIEW interface and MATLAB platform to realize the bidirectional real-time communication.

The decentralized Predictive Functional Control (PFC) strategy is then developed to coordinate the heating resistor and air extraction system. We optimized the control parameters using a hybrid adaptive differential evolution (HADE) algorithm via multi-objective optimization framework where tracking accuracy, transient performance and control smoothness were compared. The optimization strategy proposed in this paper exhibited strong abilities of convergence and adapting for nonlinear thermal dynamics.

Excellent prediction accuracy under solar irradiation and electrically assisted operating conditions was confirmed. Proposed digital twin produced root-mean-square error (RMSE) values under 0.33 °C for temperature and RMSE worse than 0.32% for humidity, with Variance Accounted For (VAF) over 99.6% across all testing scenarios. These results validate that the proposed framework is quite robust and reliable for real-time monitoring and adaptive thermal regulation.

The proposed framework has several key advantages over recent works on digital twins for thermal food processing and solar drying systems. Recent works, such as [6] are heavily inspired by predictive thermal processing for applications and they mainly focus on model simplification through the development of reduced-order digital twins or neural ordinary differential equation models that prioritize computational efficiency with little autonomy in process predictions. Digital Twin other recent studies focused mainly on data-driven monitoring, energy efficiency analysis or machine-learning-based prediction for solar dryers but did not incorporate adaptive online estimation and real-time predictive control at the same time. In contrast, the approach proposed in this paper integrates the above-mentioned EKF-based adaptive state estimation with HADE-driven optimization and decentralized PFC control within a real-time digital twin architecture. What is more, although several drying-system digital twins have been proposed for offline simulation or process monitoring applications, the current framework promotes seamless online synchronization with adaptive controller tuning and real-time thermal regulation in dynamic environments.

In summary, the results obtained prove that the proposed digital twin framework represents an efficient and accurate tool for intelligent hybrid solar drying systems and a robust base for future smart agro-industrial applications. Future work will be geared towards extending the framework towards multivariable moisture-content control, AI-assisted supervision, fault diagnosis and large-scale deployment of cloud connected digital twins on autonomous drying platforms.

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