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Smart Energy Management for Sustainable Greenhouse Operations: Optimization of Grid Energy and Battery Storage

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Abstract

Effective energy management plays a vital role in improving greenhouse (GH) performance and advancing sustainability. This study introduces an innovative multi-objective optimization strategy specifically developed for GH energy management, aiming to reduce reliance on grid energy while maximizing the battery state of charge (SOC) over a defined time period. The optimization framework incorporates decision variables, including network power, battery power, and battery energy, while respecting constraints on battery capacity, initial energy levels, and the minimum and maximum energy limits of the battery storage system. The performance of a smart energy management system (EMS) is assessed by comparing it against conventional optimization techniques. Critical hyperparameters for the optimization process—such as plateau time, prediction time, and optimization time—are identified using the ellipse optimization technique. By modeling the GH as a microgrid, the study examines relevant energy management metrics and load profiles. Simulations performed in MATLAB Simulink (R2021b) reveal substantial improvements, with the smart EMS reducing the objective function by more than 50% relative to traditional EMS approaches. Furthermore, the proposed EMS demonstrates strong robustness under varying load power and irradiation patterns. Even in partial-shading scenarios, the system remains adaptable, with a maximum increase in the objective function of only 0.35553%. Matching the photovoltaic (PV) system output power to realistic field conditions further confirms the EMS's practical effectiveness. These results highlight the smart EMS's capability to optimize energy use in GH settings, paving the way for more sustainable energy management solutions. This work advances energy optimization techniques in agricultural contexts, supporting greater resource efficiency and environmental responsibility.

Keywords Optimization, PV, Smart energy management system, Greenhouse, Battery energy storage

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Introduction

Background and motivations

The integration of renewable energy sources (RESs), such as photovoltaic (PV) systems, wind power, and battery storage, into small- and medium-scale electricity networks offers multiple benefits, including lower energy costs and improved resilience against outages [1, 2]. Greenhouses represent one promising application area for these RES technologies. Greenhouse farming is essential for ensuring a consistent food supply by maintaining a controlled environment that supports ideal plant development. Nevertheless, the high energy requirements of GH operations present a major obstacle, driving the need for creative strategies to boost energy efficiency. The pursuit of sustainability has

encouraged researchers to explore the combination of RESs with sophisticated energy management systems (EMSs) [3]. In this context, the present study contributes by introducing a smart EMS tailored to enhance solar energy utilization within GH facilities.

With global food demand continuing to grow and pressure to reduce agriculture’s ecological footprint intensifying, efforts to improve the sustainability of GH operations have gained momentum. Much of the energy consumed in greenhouses comes from traditional grid sources, which significantly affect both operating costs and greenhouse gas emissions. To address this issue, there is rising interest in employing RESs—particularly solar power—to supply energy for GH operations [4]. Effective use of such intermittent renewable sources requires advanced EMSs capable of matching supply with demand while accounting for the variable energy requirements typical of greenhouse settings. **Figure 1** illustrates a schematic diagram of RES integration in a smart GH [5].

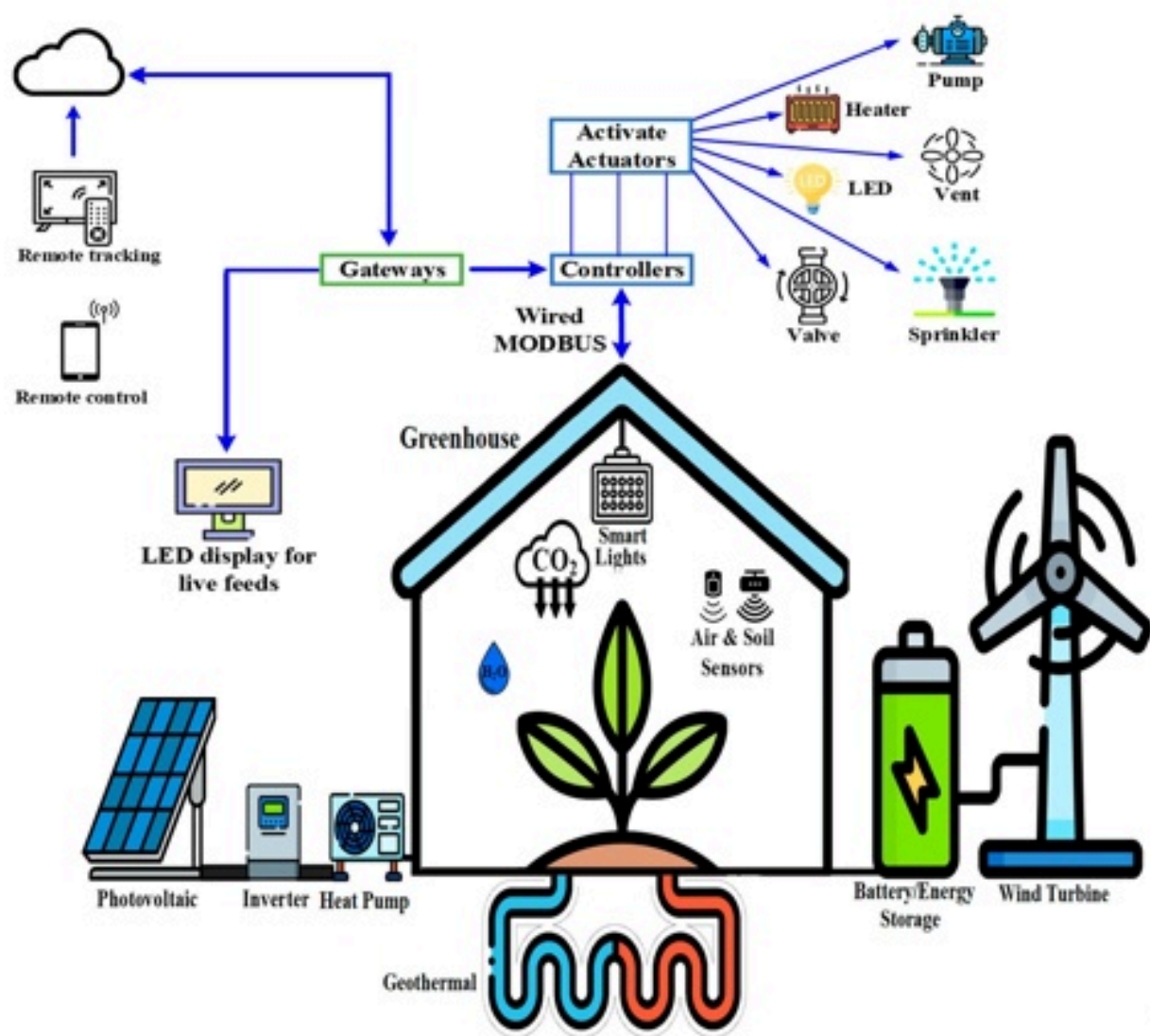


Figure 1. A schematic of integrating RESs in a smart GH.

Literature review of energy management in GHs

Earlier research has examined multiple dimensions of energy management within greenhouses, placing particular focus on the incorporation of renewable energy sources (RESs). Prominent studies, including those by Smith *et al.* [6] and Wang *et al.* [7], have evaluated the viability of geothermal energy for greenhouse use, underscoring its benefits related to long-term sustainability and economic efficiency. Nonetheless, the combined optimization of energy use via intelligent systems alongside geothermal sources continues to receive limited attention.

Within the field of energy management systems (EMS), conventional optimization methods have long been applied to improve energy performance across diverse applications. However, the adoption of advanced smart EMSs—which integrate machine learning and forecasting techniques—is increasingly recognized for their capacity to respond effectively to fluctuating environmental variables. Research by Li and Wang [8] and Chen *et al.* [9] demonstrates the strong performance of smart EMS across a range of energy optimization contexts, inspiring the current investigation into their suitability for greenhouse environments.

Greenhouse farming, which plays a vital role in global food security, faces the ongoing challenge of reducing energy use to achieve greater sustainability and cost-effectiveness. The adoption of smart EMSs, combined with targeted optimization techniques, represents a highly promising direction, delivering multiple benefits over conventional methods [5]. These benefits can be categorized as follows:

- **Enhancing Resource Utilization and Adaptability:** Smart EMSs applied in greenhouse settings enable accurate management of resources by synchronizing energy consumption with real-time requirements. This approach optimizes the use of electricity, heating, and other inputs, thereby reducing waste and lowering operating expenses. A major strength of these intelligent systems is their ability to adapt in real time to changing external conditions. Leveraging live sensor data and predictive models, they dynamically modulate energy allocation according to variables such as temperature, humidity, and solar availability, ensuring efficient performance across diverse scenarios [10, 11].
- **Optimized Crop Growth and Yield:** Smart EMSs support enhanced plant development by customizing the growing environment to match the precise requirements of different crops. Investigations by Sofwan *et al.* [12] demonstrate the favorable effects of intelligent control systems on agricultural output, thanks to their ability to finely regulate parameters including temperature, lighting intensity, and CO₂ concentration.
- **Reduction in Environmental Footprint:** By eliminating wasteful energy practices and prioritizing renewable energy sources, smart EMSs help decrease the overall ecological impact of greenhouse gas activities. Incorporating RESs, such as solar energy, supports broader sustainability objectives and reduces the environmental burden associated with GH production [13, 14].
- **Cost Savings and Economic Viability:** Intelligent EMSs deliver clear financial benefits through improved energy efficiency and decreased reliance on grid-supplied power. Over extended periods, these reductions in energy expenditure improve the profitability and long-term economic stability of greenhouse enterprises [15, 16].
- **Mitigation of Energy Price Volatility:** The application of optimization techniques reduces exposure to fluctuations in external energy markets by increasing self-sufficiency. This stability is especially valuable for greenhouse managers, as it facilitates more reliable budgeting and financial forecasting [17].
- **Real-Time Monitoring and Control:** Smart EMSs provide continuous oversight and immediate adjustment of energy flows, enabling rapid responses to changes in demand or unexpected disruptions. Such responsiveness strengthens system robustness and ensures consistent, dependable operation of greenhouse infrastructure [18].
- **Integration of Machine Learning for Predictive Analysis:** By embedding machine learning within smart EMSs, it becomes possible to forecast future energy needs based on patterns derived from past performance and environmental trends.

This forward-looking capability enhances the planning of energy allocation and storage strategies inside the greenhouse [19].

- **Improved Operational Efficiency:** The detailed regulation offered by smart systems leads to higher overall operational performance. Automating demanding tasks, such as climate control, reduces the need for manual oversight, freeing greenhouse personnel to focus on higher-level planning and crop care [10, 20].
- **Technological Innovation and Industry Leadership:** Operators who implement smart EMSs establish themselves at the forefront of agricultural technology. By adopting state-of-the-art tools, they help drive progress toward more sustainable farming methods and establish exemplary industry standards [21].

In light of the challenges and opportunities outlined above, this paper addresses the following four key research questions:

- How can solar energy integration be optimized to decrease reliance on traditional electricity grids and improve the environmental sustainability of greenhouse operations?
- What are the primary benefits and possible limitations of deploying a smart EMS for greenhouse energy optimization, especially when compared with conventional optimization techniques?
- In what ways can the careful selection and tuning of critical hyperparameters—such as plateau time, prediction time, and optimization time throughout the day—enhance the flexibility and effectiveness of a smart EMS in managing greenhouse energy?
- Which concrete results or measurable indicators demonstrate the superior energy efficiency and operational improvements delivered by the proposed multi-objective optimization framework designed specifically for greenhouse energy management?

To address these questions, the present study fills an important gap in the current body of knowledge by introducing a multi-objective optimization framework specifically designed for greenhouse energy management. The approach integrates solar energy utilization with a smart EMS. The sections that follow describe the proposed methodology, report simulation outcomes, and provide a thorough evaluation of the system's advantages relative to standard optimization methods.

Motivation and main contributions

The primary motivations behind this paper stem from several critical aspects:

- **Multi-Objective Optimization for GH Energy Management:** The study proposes a novel multi-objective optimization framework designed to simultaneously reduce grid energy consumption and maximize the battery state of charge (SOC) over a given time horizon. This method promotes more thorough and effective management of energy resources in greenhouse operations.
- **Integration of Solar Energy:** A key contribution of this work is the incorporation of solar energy as the main renewable input within the developed EMS. By leveraging the reliability and environmental friendliness of solar power, the proposed system aims to reduce reliance on traditional electricity grids and thereby enhance the sustainability profile of greenhouse operations.
- **Smart EMS:** This paper presents and evaluates a smart energy management system (EMS) tailored for optimizing energy use in greenhouses. The system employs sophisticated techniques, such as machine learning and predictive modeling, to dynamically regulate energy consumption in response to changing environmental factors. This distinguishes

it from conventional optimization strategies and paves the way for more adaptive and intelligent energy management solutions.

- **Identification and Optimization of Hyperparameters:** The research identifies and fine-tunes essential hyperparameters that are vital to the performance of the proposed EMS. Key parameters—including plateau time, prediction time, and optimization time throughout the day—are optimized using the ellipse optimization method. This tuning process significantly boosts the system's flexibility and operational efficiency across diverse conditions.

In addition, the main contributions of this paper encompass the following:

- Simplifying the objective function and limiting decision variables to those that are independent.
- Defining the relevant hyperparameters and identifying their optimal values.
- Incorporating uncertainty in the forecasted values of photovoltaic power (Ppv) and load power.
- Taking into account environmental influences, including partial shading effects.
- Continuously updating the advanced predictions of Ppv throughout the day.

Overall, this paper addresses multiple real-world dimensions of the energy management challenge to deliver a solution that is practical, high-performing, and feasible for actual implementation. Through a comprehensive strategy that combines multi-objective optimization, solar energy utilization, advanced smart EMS with cutting-edge algorithms, and careful tuning of critical hyperparameters, the work seeks to advance integrated, sustainable approaches to greenhouse energy management while achieving maximum energy efficiency.

Problem Definition and Methodology

Efficient energy management in greenhouse (GH) operations is fundamental to contemporary agriculture and long-term environmental sustainability. As the world's population steadily increases, food demand continues to grow, underscoring the essential role of greenhouse farming in global food security [22]. Nevertheless, the traditional high-energy practices employed in GHs create substantial economic and ecological difficulties.

Proper regulation of energy use is essential for reducing operational expenses and lessening the environmental burden associated with conventional electricity sources. GH managers face the ongoing challenge of balancing the requirements for ideal plant development with the need to curb energy-related costs. The growing need to adopt more sustainable methods has spurred considerable research into integrating renewable energy sources (RESs) into greenhouse systems [23].

This study addresses that need by introducing a smart energy management system (EMS) specifically designed for greenhouse settings. Central to this approach is the utilization of solar energy, valued for its consistent availability. Through a multi-objective optimization framework, the paper aims to reduce dependence on external power grids, improve battery storage performance, and advance broader environmental sustainability in greenhouse operations. The value of this research lies in its capacity to transform energy-use patterns in GHs, supporting more cost-effective and environmentally sound agricultural practices.

In the sections that follow, we outline an optimized strategy to tackle these challenges.

Throughout this article, the terms “solar energy” and “PV” are employed. “Solar energy” denotes energy obtained from the sun in a broad sense, whereas “PV” refers specifically to the photovoltaic technology that transforms sunlight into

electrical power. In the context of our work, these terms are used interchangeably to encompass both the general notion of solar energy and the particular application of PV systems.

Objective function for multi-objective optimization

To deliver an effective energy optimization solution for the greenhouse, the core objective of this study is to minimize the cost of grid-supplied power while simultaneously maximizing the battery state of charge (SOC) at the end of the day. This dual focus reflects the combined aims of reducing reliance on external electricity supplies and enhancing battery storage utilization within the GH environment. The battery SOC is calculated according to [Eq. 1 \[24\]](#).

$$SOC_{batt} = E_{batt} / C_{batt} \quad (1)$$

SOC_{batt} , the battery state of charge, is expressed as the ratio of the current battery energy, E_{batt} , to the battery's total capacity, C_{batt} . This formulation ensures equilibrium between stored energy and the battery's overall capacity. Battery energy and power are further governed by constraints expressed in [Eq. 2](#):

$$\begin{aligned} E_{min} &\leq E_{batt} \leq E_{max} \\ P_{min} &\leq P_{batt} \leq P_{max} \end{aligned} \quad (2)$$

Here, E_{min} and E_{max} indicate the minimum and maximum allowable battery energy levels, respectively. Similarly, P_{min} and P_{max} represent the minimum and maximum permissible battery power limits, respectively.

These constraints ensure that both the battery's energy level and power output remain within the acceptable operational boundaries defined by its design specifications. The formulation accounts for the battery's initial energy state and the inherent limitations of the storage system.

Energy Management System (EMS)

EMSs operate at different hierarchical levels depending on the scale of application, ranging from residential buildings and commercial facilities to industrial plants and entire districts. As illustrated in [Table 1](#), these systems can interconnect models representing EMSs across multiple tiers and varying degrees of sophistication [\[25\]](#).

An EMS constitutes an integrated framework responsible for monitoring, regulating, and optimizing both energy consumption and generation across diverse settings. It integrates hardware components, software tools, and operational procedures to deploy energy assets while preserving required performance standards efficiently. The central purpose is to reduce energy expenditures, minimize adverse environmental effects, and enhance overall system effectiveness [\[26, 27\]](#). EMSs are broadly categorized into traditional and smart types, with increasing preference for intelligent solutions as electrification expands. Conventional EMSs depend on fixed rules and operate without access to live data, whereas the shift toward smart EMSs emphasizes adaptive strategies. These include demand forecasting, dynamic electricity tariffs, optimization-driven techniques, and real-time measurements to enable fully automated decision-making [\[28\]](#). Such advanced practices are already commonplace in large-scale utility operations, where generation schedules are adjusted according to load patterns and market prices. This same principle can be readily scaled down to smaller systems, such as microgrids, and extended to a wide range of applications. The fundamental aim of smart EMSs is to maintain ongoing surveillance of energy demand and system responses, thereby continuously refining overall performance [\[29\]](#). Through this iterative optimization loop, multiple benefits can be realized, including energy conservation, emission reductions, and

cost minimization. **Figure 2** presents an overview of different EMS methodologies, with the traditional approach shown on the left.

Table 1. EMS levels.

Definition	Stands for	Read
HEMS	Home EMS	“hemz”.
BEMS	Building EMS	“bemz”.
FEMS	Factory EMS	“fems”.
CEMS	Cluster/Community EMS	“seems”.

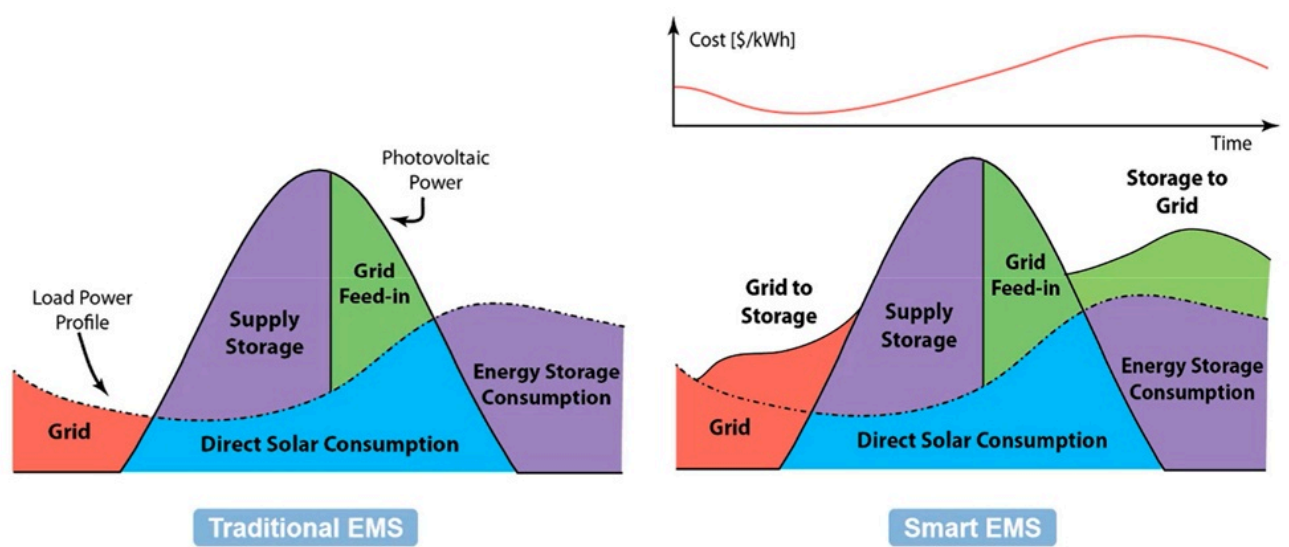


Figure 2. EMS logic in traditional and smart states [30].

The figure shows the load power profile (dotted line) alongside the PV power input. The load typically peaks in the afternoon and evening, coinciding with periods of residential occupancy. During peak solar irradiance—especially on clear days—the PV contribution is maximized during periods of elevated demand. The shaded areas highlight the behavior of the conventional heuristic-based management strategy. In the early morning, grid power supplies the base load. When demand is low, and solar generation becomes available, PV energy is used directly to meet needs while excess is directed to charge the storage system. At a designated threshold, surplus energy is exported to the grid. Later in the evening, the stored energy is discharged to offset demand. The smart strategy, shown on the right, additionally factors in electricity pricing. For example, during low-price intervals, grid power may be intentionally used to charge storage, with discharge and potential grid export occurring when prices rise.

In the present study, the focus is placed on optimizing an EMS configured for a microgrid architecture. This microgrid integrates PV arrays, battery energy storage, several residential loads, and a connection to the main utility grid. It is assumed that the underlying power electronic converters and interfaces are already in place, allowing the EMS to operate at a supervisory level with a system-wide perspective. Optimization is achieved through a decision-making algorithm that leverages predictive information and forecasts to schedule charging and discharging actions intelligently, determine

optimal timing for grid interaction, and maximize overall energy efficiency. The approach respects all relevant operational constraints and strives to deliver the most effective coordinated strategy for utilizing the microgrid's diverse components.

The high-level control logic forms the backbone of the EMS, coordinating the interplay among all elements to ensure smooth, efficient, and optimized microgrid performance [31]. To further strengthen the optimization process, this work adopts a smart EMS formulation to achieve superior efficiency. The core objective remains minimizing grid electricity costs while simultaneously maximizing the battery's final state of charge (SOC), as expressed in Eq. 3.

$$f_{obj} = cost \times P_{grid} - w_{Final} \times SOC_{batt}(N) \quad (3)$$

Where P_{pv} , P_{batt} , and P_{load} represent the power delivered by the PV array, the battery, and the load, respectively, and w_{Final} is a weighting coefficient. In addition, several constraints must be satisfied, one of the most important being the power balance condition expressed as:

$$P_{pv} + P_{grid} + P_{batt} = P_{load}. \quad (4)$$

The decision variables must be mutually independent, meaning the value assigned to one variable must not influence the value of another. Keeping the number of decision variables as small as possible helps reduce problem complexity. Including dependent variables compromises the accuracy of the EMS algorithm, whereas incorporating unnecessary dependencies increases both computational load and execution time. Notably, E_{batt} and P_{batt} are interdependent variables. Meanwhile, P_{grid} can be directly derived from Eq. 4. Given that fixed profiles for P_{load} and P_{PV} are assumed at each optimization step, the objective function f_{obj} can be formulated accordingly.

$$f_{obj} = cost \times \left(\frac{P_{load} - P_{PV} - P_{batt}}{Constant} \right) - w_{Final} \times SOC_{batt}(N). \quad (5)$$

The value of P_{batt} that minimizes f_{obj} will also minimize the following expression.

$$f_{new} = -cost \times P_{batt} - w_{Final} \times SOC_{batt}(N). \quad (6)$$

Since energy corresponds to the time integral of power (i.e., the accumulated power over a defined interval), the battery energy can be expressed accordingly.

$$E_{batt}(N) = -dt \sum_{i=1}^{N-1} P_{batt}(i) + E_{int}. \quad (7)$$

By combining Eq. 1 and 7, the modified objective function f_{new} can be rewritten as follows.

$$f_{new} = -cost \times P_{batt} - w_{Final} \times \left(-dt \sum_{i=1}^{N-1} P_{batt}(i) + \frac{E_{int}}{Constant} \right) / C_{batt}. \quad (8)$$

Thus, the P_{batt} value that minimizes f_{obj} also minimizes f_{new} as defined in Eq. 8. After eliminating the constant term, the expression simplifies to:

$$F_{New} = -cost \times P_{batt} + w_{Final} \times dt P_{batt}(i) / C_{batt}. \quad (9)$$

The P_{batt} minimizing f_{obj} will likewise minimize F_{New} as given in Eq. 9. Consequently, the optimization problem can be stated in the following form:

$$\begin{aligned} \min_{P_{batt}} F_{New} &= -cost \times P_{batt} + w_{Final} \times dt \sum_{i=1}^{N-1} P_{batt}(i) / C_{batt}. \\ \text{subject to : } \forall n, &\begin{cases} E_{min} \leq -dt \sum_{i=1}^{n-1} P_{batt}(i) + E_{int} \leq E_{max} \\ P_{min} \leq P_{batt}(n) \leq P_{max} \end{cases} \end{aligned} \quad (10)$$

The optimization procedure determines the decision variables over the prediction horizon T_{pred} , assuming they remain constant throughout the plateau duration $T_{plateau}$. The entire optimization routine is repeated at regular intervals defined by the optimization time T_{opt} . The key hyperparameters governing this process are T_{pred} , $T_{plateau}$, and T_{opt} .

Owing to the high dimensionality of the problem, certain numerical techniques—such as Bayesian optimization—involve considerable computational expense when solving the optimization problem Eq. 10 to compute the decision variable P_{batt} at every time step. To address this, the following MATLAB functions are applied to optimize the decision variables, yielding virtually equivalent results:

- “fmincon”: employed to locate the minimum of a constrained nonlinear multivariable function.
- “fminimax”: used to resolve minimax constrained optimization problems.
- “solve”: applied to tackle general optimization or equation-solving tasks.

T_{pred} is treated as a variable-length variable and set equal to the remaining hours of the day, since grid electricity prices peak during the final hours of the day. It follows that $T_{pred} < T_{opt} < T_{plateau}$.

The Bayesian optimization technique is applied to determine the optimal values of $T_{plateau}$ and T_{opt} using the “bayesopt” function in MATLAB. This method represents a robust numerical approach to optimization, enabling efficient exploration of the search space by prioritizing the most promising regions while accounting for uncertainty and incorporating prior information.

To evaluate the performance of the proposed intelligent strategy, the conventional EMS algorithm is illustrated in Figure 3. Similarly, Figure 4 depicts the operational workflow of the smart EMS. Over the course of 24 hours, the optimization procedure is executed at intervals of T_{opt} . At each optimization instant (t_i), the objective is to minimize the grid power cost across the subsequent prediction interval T_{pred} . The resulting optimal battery power value is then applied at t_i and held constant until the next optimization step, during which the battery state of charge (SOC) is updated. For every optimization cycle, the SOC value at the current instant t_i is known and used as the starting point.

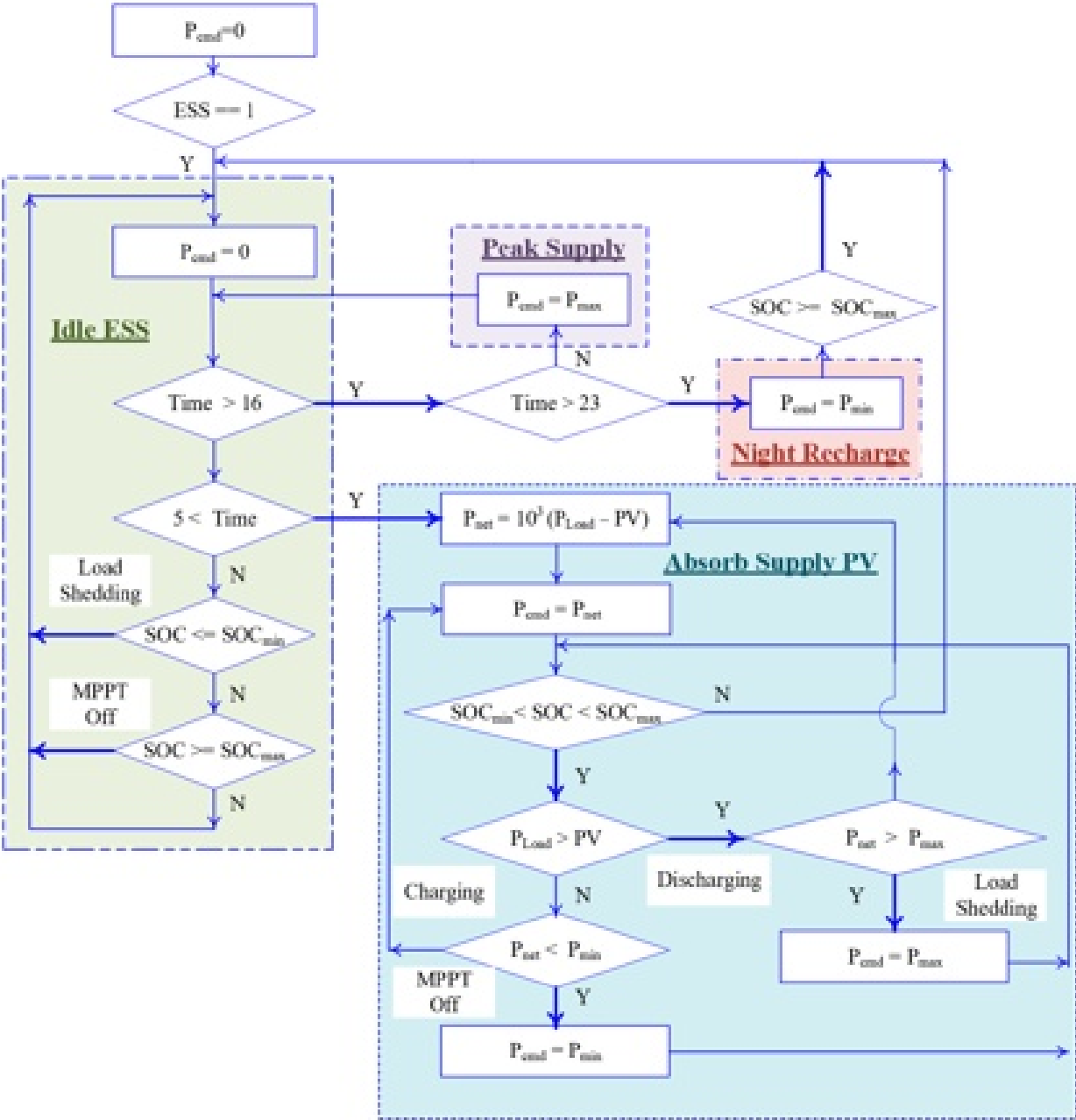


Figure 3. Traditional EMS algorithm.

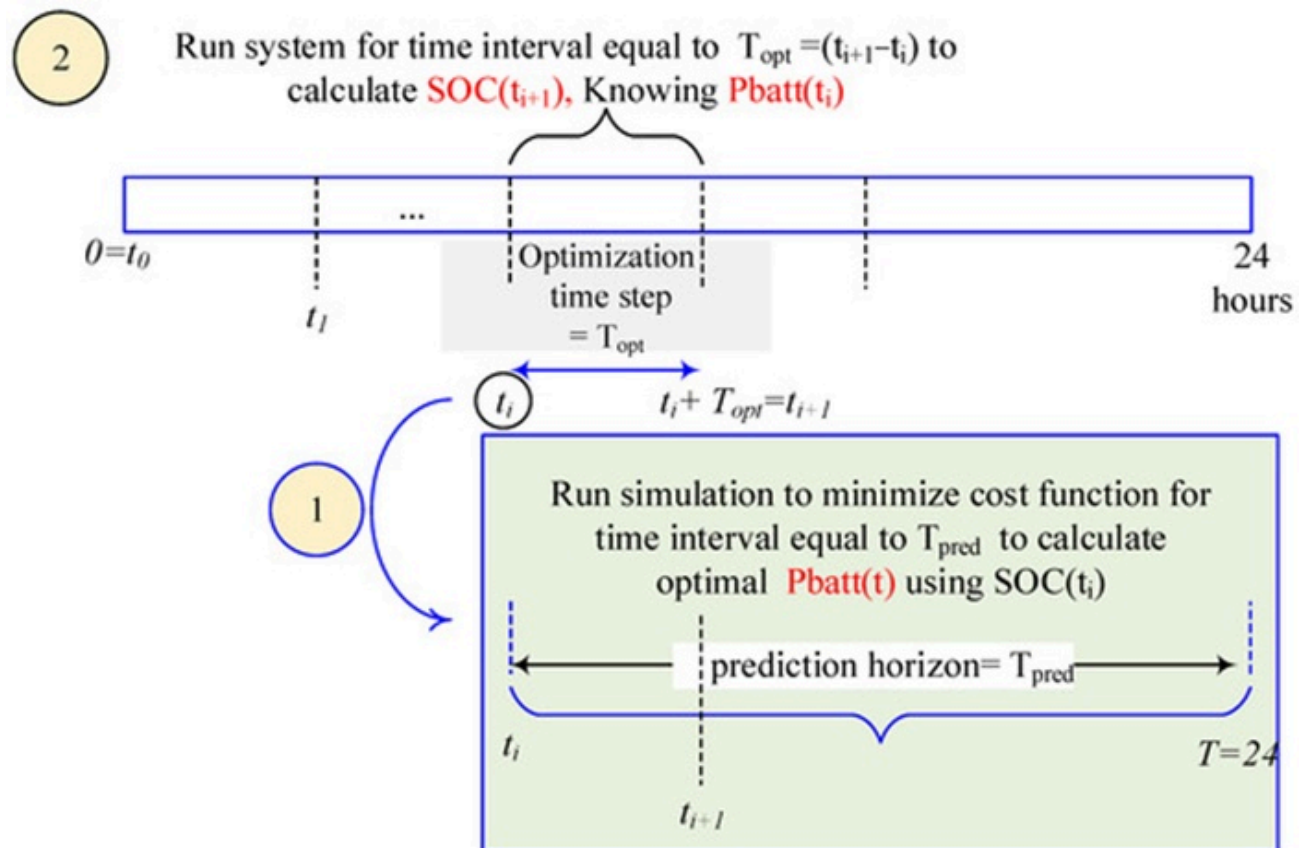


Figure 4. Smart EMS procedure

Results and Discussion

To demonstrate the outcomes of the simulations, we present and compare two distinct operational modes: the smart energy management approach and the conventional energy management approach. Figure 5 shows the implementation of the EMS strategies for greenhouses within the Simulink environment. As previously noted, by incorporating relevant energy management metrics and load characteristics, the greenhouse can be effectively modeled as a microgrid. A simple microgrid configuration has been developed in Simulink for this purpose. This model allows observation of system behavior under both the traditional rule-based EMS and the optimization-driven smart EMS, facilitating a direct performance comparison between the two methods. The model includes a variable load representing residential households, a constant base load that remains unchanged over time, and a photovoltaic array serving as the renewable input source, capable of adopting different irradiance profiles (corresponding to clear-sky and overcast conditions), as shown in Figure 6.

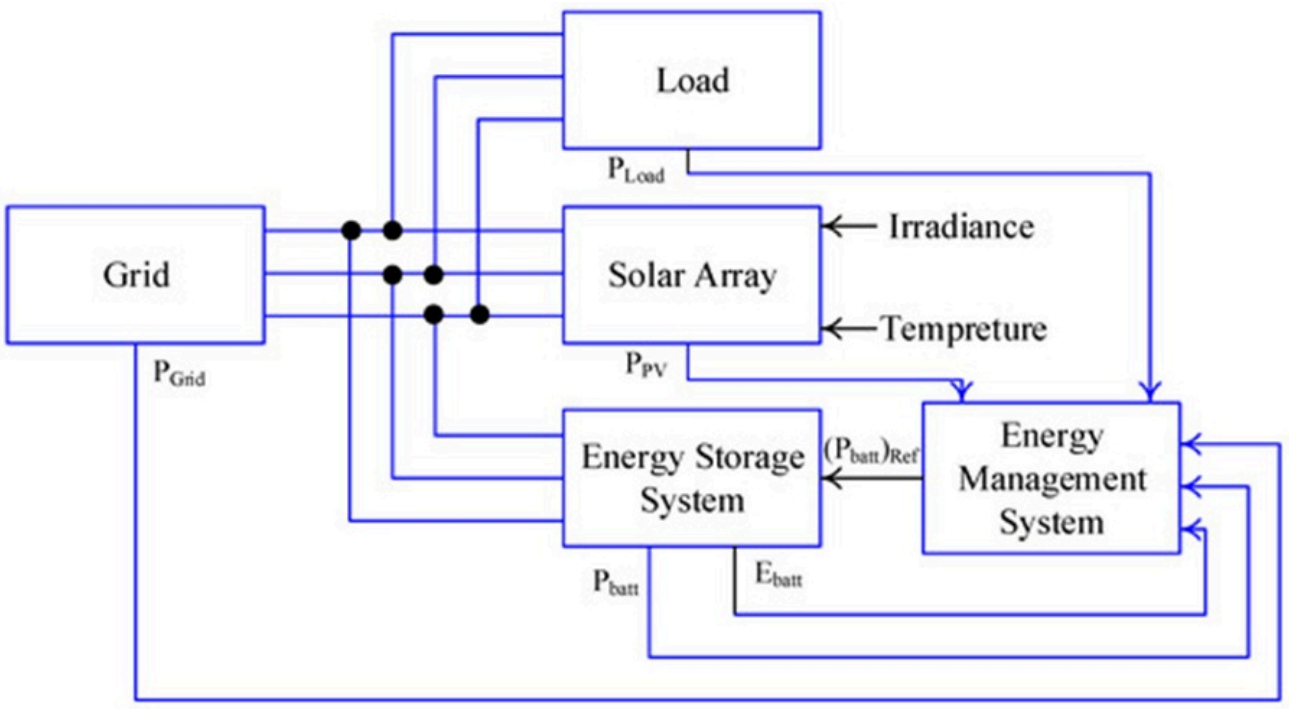


Figure 5. Implementing EMS approaches for GHs in Simulink.

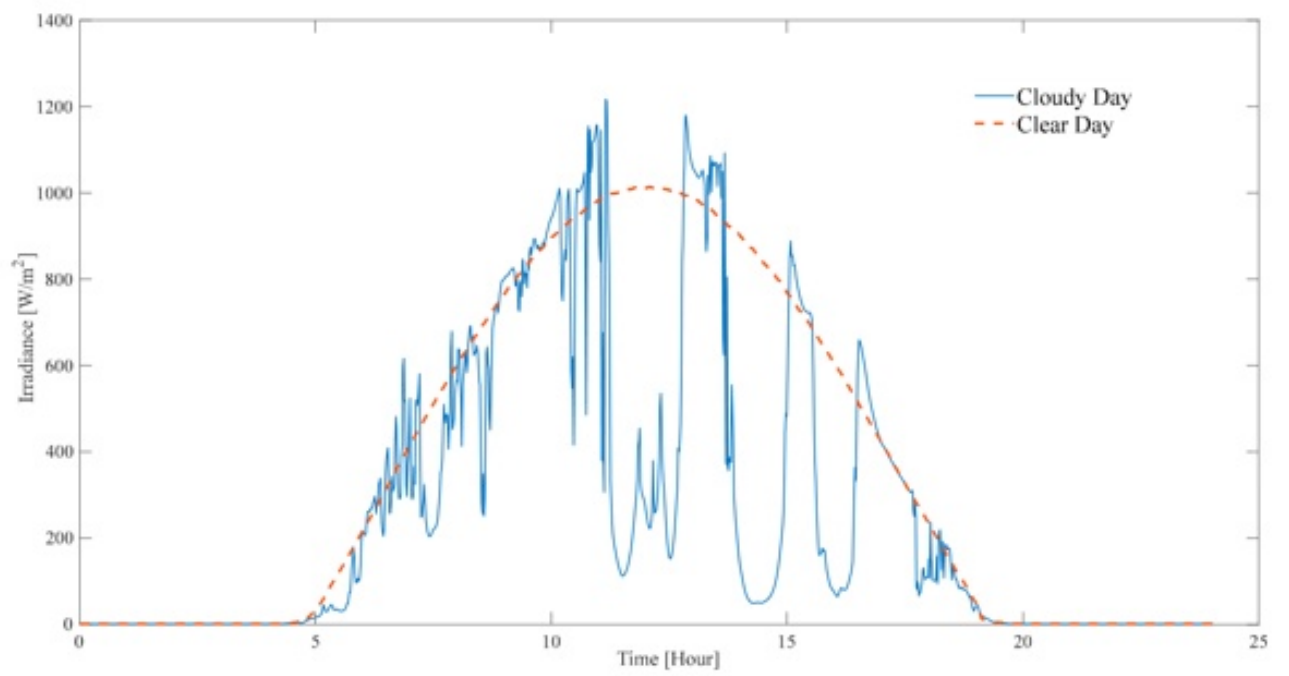


Figure 6. Comparison of the irradiance profile on a clear and cloudy day.

Figure 7 presents the load profile used in the case study. In contrast, Figure 8 shows how grid electricity costs vary with different settings of the prediction horizon T_{pred} and the optimization interval T_{opt} . These results highlight the critical importance of tuning these hyperparameters. It is clear that prolonging the prediction horizon significantly increases the computational demand. Nevertheless, since electricity prices typically peak in the final hours of the day, it is essential to

include this high-cost period in T_{pred} to maintain prediction accuracy. Consequently, the prediction horizon T_{pred} is treated as a dynamic parameter, set equal to the remaining duration of the day. As a result, T_{pred} reaches its maximum early in the morning and gradually decreases throughout the day.

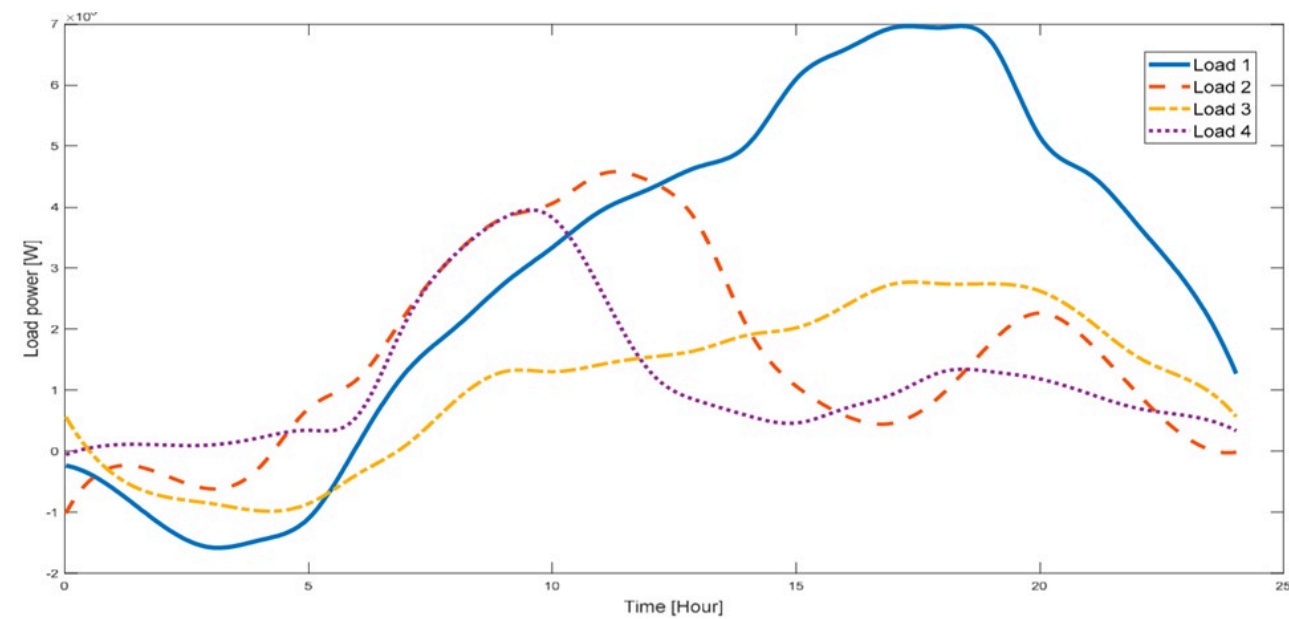


Figure 7. Load profiles of the study case.

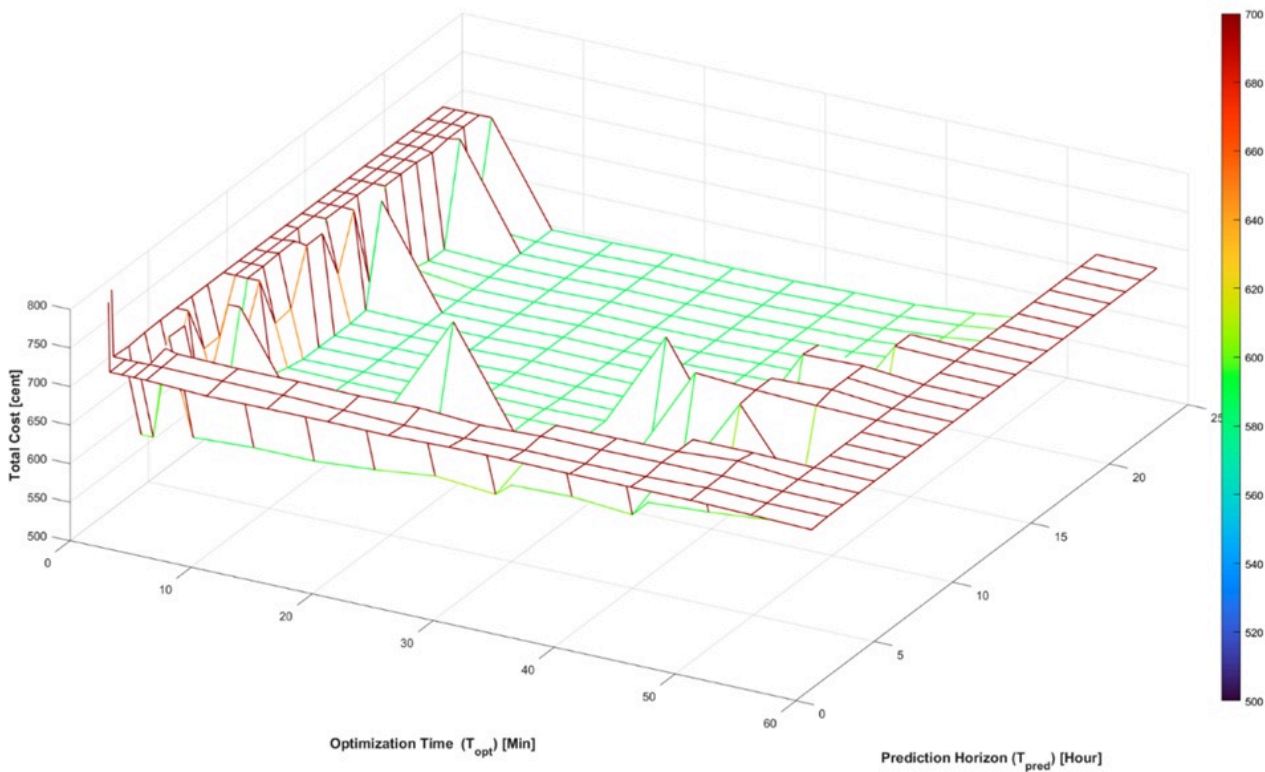
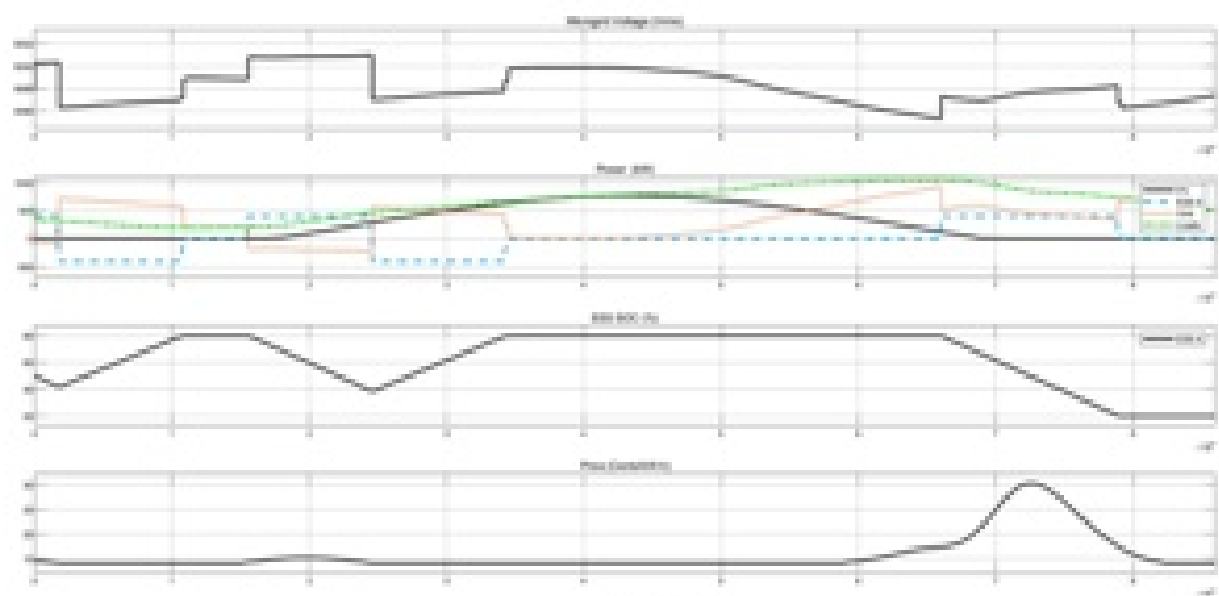
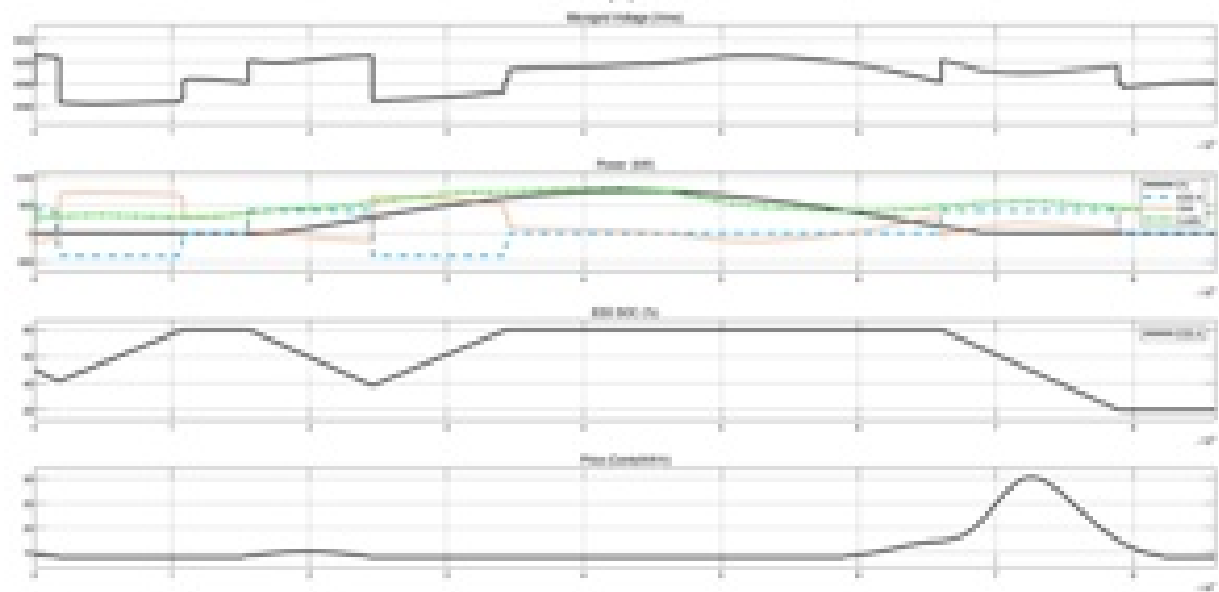


Figure 8. Impact of prediction horizon and optimization time on grid power costs.

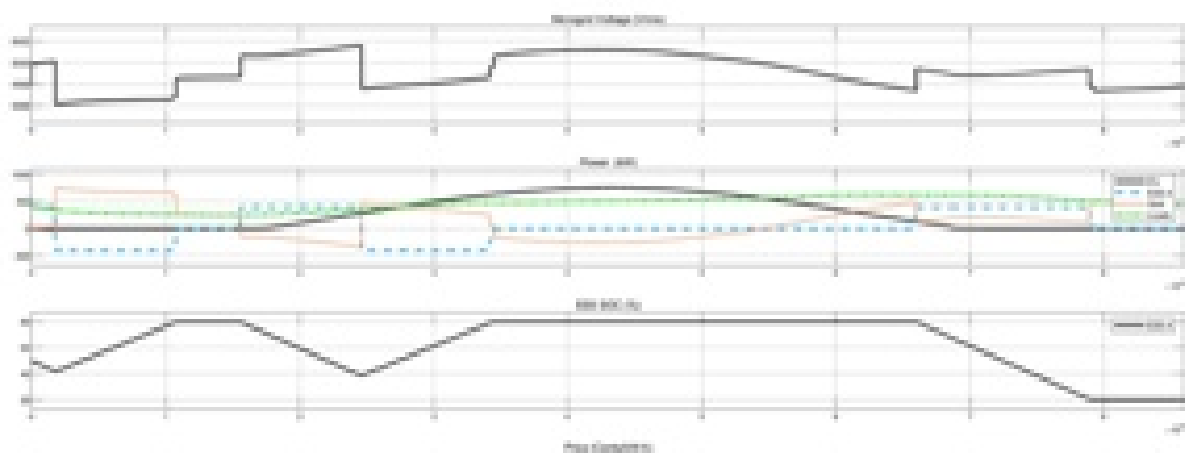
Figure 9 provides a detailed overview of key parameters in the microgrid system, including microgrid voltage, PV power output, battery state of charge, grid power exchange, and load demand.

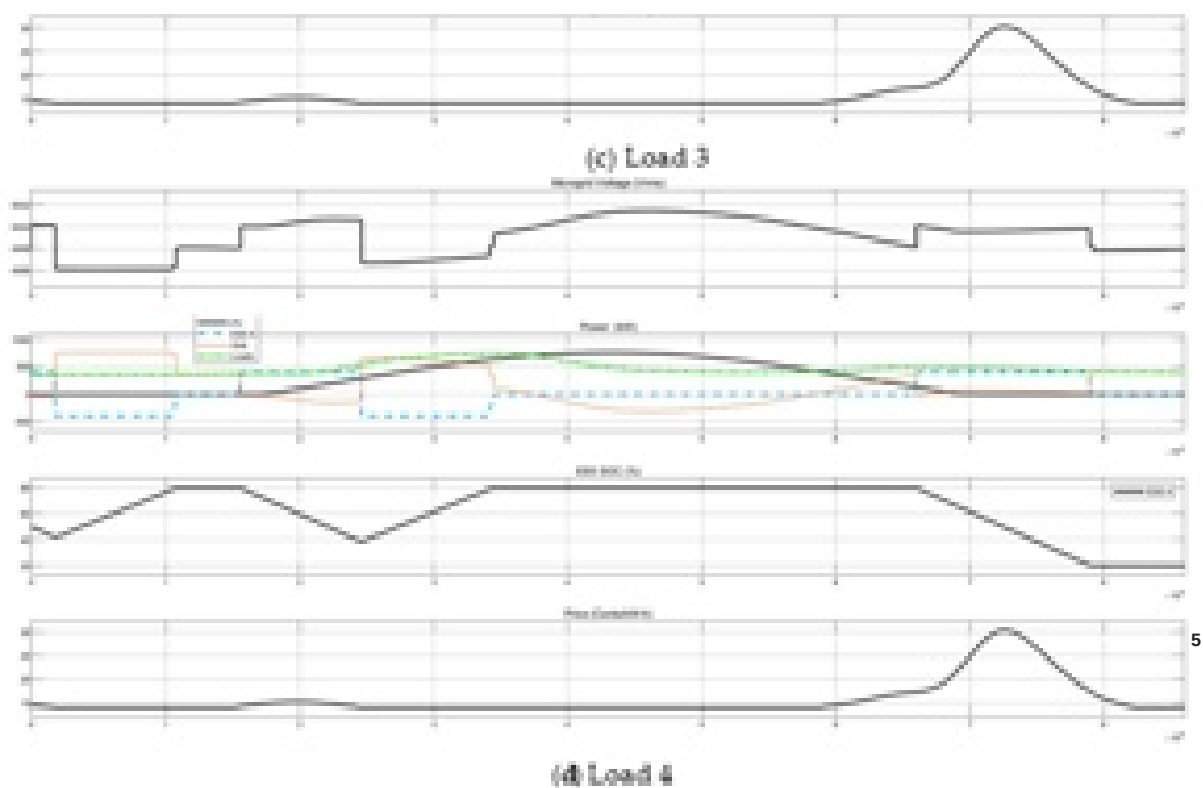


(a) Load 1



(b) Load 2





Smart	1	19.578 14.581	13.544 7.5281	19.988 19.988	10.252 7.7079
	2	12.745	6.1231	19.988	7.7163
	3				
	4	13.604	5.8376	19.988	4.2615

To better reflect realistic operating conditions, a $\pm 10\%$ tolerance has been applied to both the load power and irradiance profiles, as depicted in [Figure 10](#). The corresponding numerical outcomes are presented in [Table 3](#), with T_{plateau} and T_{opt} both set to 5 minutes. Despite these intentional variations in load power and solar irradiance, the objective function value remains notably stable. This stability demonstrates the robust, reliable performance of the proposed EMS under realistic disturbances.

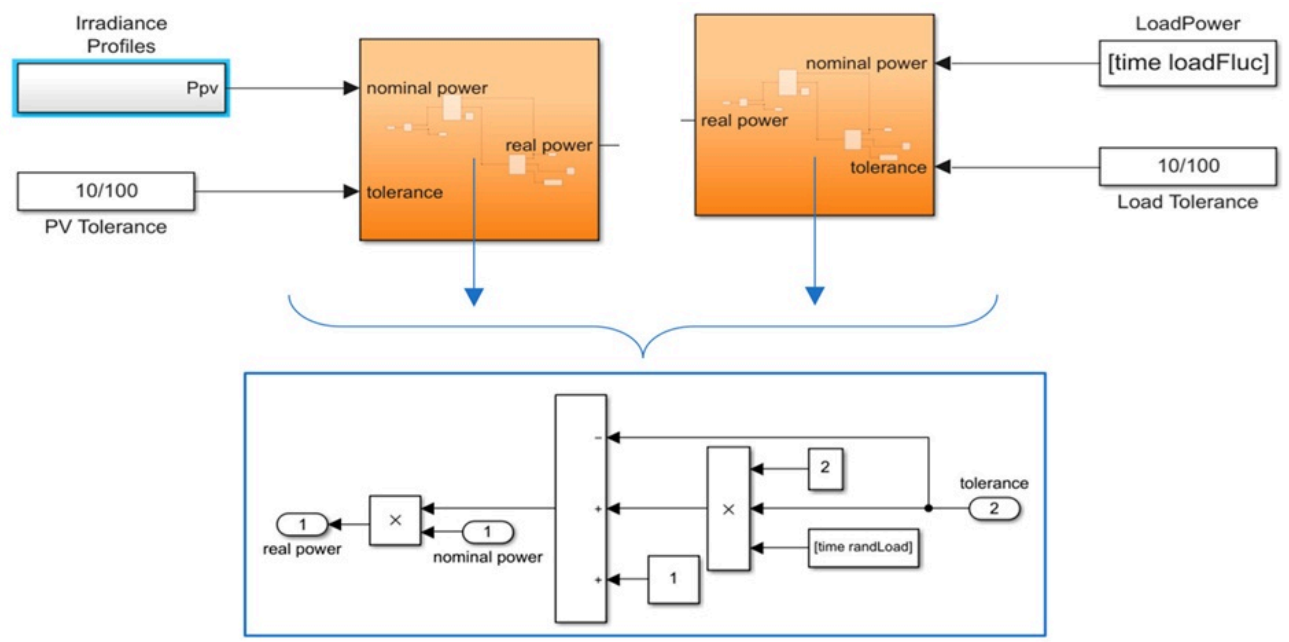


Figure 10. Irradiance and load power with 10% tolerance.

When the simulation is repeated with a partial shading event lasting 30 minutes beginning at 11 a.m.—as shown in **Figure 11**—the results are summarized in **Table 4**. The findings indicate that partial shading causes only a modest increase of 0.35553% in the objective function. This minimal rise underscores the proposed EMS's strong adaptability and resilience in responding effectively to natural phenomena, such as partial shading.

Table 3. Simulation result for irradiance and load power with 10% tolerance.

Load #	Scenario type	Execution time [s]	fobj	Final SOC [%]	Total grid power × 10 ⁵ W
1	Tolerated nominal	32.324	13.534	19.988	18.892
		11.344	13.544	19.988	10.252
2	Tolerated nominal	28.639	7.5014	19.988	10.710
		12.036	7.5281	19.988	7.7079
3	Tolerated nominal	31.705	6.1091	19.988	8.2816
		11.605	6.1231	19.988	7.7163
4	Tolerated nominal	30.832	5.8210	19.988	6.7372
		11.108	5.8376	19.988	4.2615

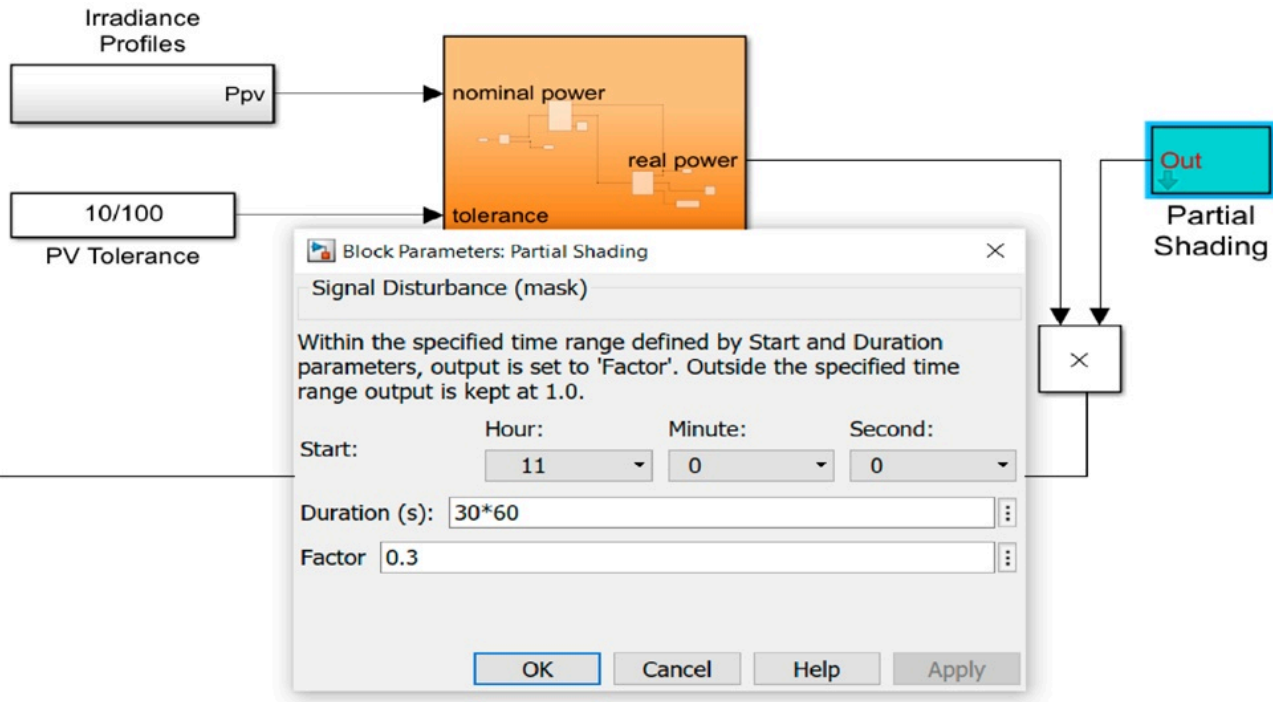


Figure 11. Partial shading at 11 a.m. for 30 min.

Table 4. Simulation result for partial shading at 11 a.m. for 30 min.

Load #	Scenario type	Execution time [s]	$fobj \times 102$	Total battery power $\times 10^5$ W	Total grid power $\times 10^5$ W
1	Nominal partial shading	13.257 13.221	13.538 13.908	1.4670 2.5270	16.987 18.754
2	Nominal partial shading	13.191 12.980	7.5013 7.8723	7.7943 7.7484	12.103 12
3	Nominal partial shading	13.030 13.128	6.1090 6.4824	0.97056 6.9664	5.1738 8.5215
4	Nominal partial shading	13.332 12.852	5.8193 6.1933	0.15922 7.7911	4.1085 7.9544

As anticipated, the drop in PV power output during shading leads to greater reliance on grid power and increased battery discharge to maintain power balance. Figure 12 provides a side-by-side comparison of PV power, battery power, grid power, load power, and battery SOC, both with and without partial shading, specifically for Load 2.

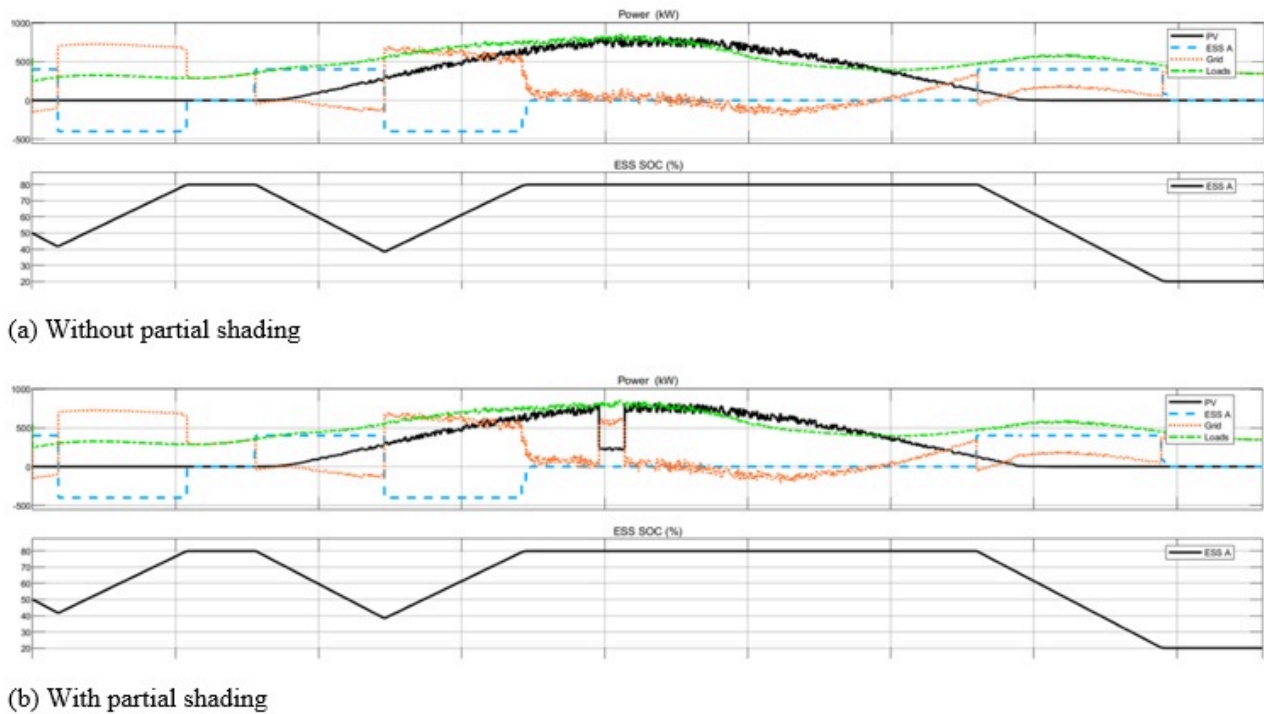


Figure 12. Comparing power and SOC with (a) and without (b) partial shading for Load 2.

Initial forecasts of irradiance and temperature are used to estimate photovoltaic power (P_{pv}). Recognizing that forecasts are not always accurate, three distinct scenarios are examined as follows:

- Case 1: P_{pv} prediction is nearly accurate. The initial P_{pv} forecast is used throughout the optimization.
- Case 2: P_{pv} prediction is inaccurate. The initial (incorrect) P_{pv} forecast is used for optimization.
- Case 3: P_{pv} prediction is inaccurate. An updated P_{pv} forecast is employed during optimization.

It is assumed that the PV power forecast is revised at 11 a.m., with the updated value reduced to 70% of the original prediction. The numerical simulation results for these cases across various optimization time steps are compared in [Table 5](#). The corresponding battery power profiles for Cases 1, 2, and 3 are shown in [Figures 13–15](#). These results highlight the critical role of refreshing the P_{pv} forecast in shaping the objective function value. Timely updates are essential for aligning the model with actual conditions and achieving superior performance. Moreover, the findings demonstrate the substantial influence of the chosen optimization time step on both the objective function value and computational runtime.

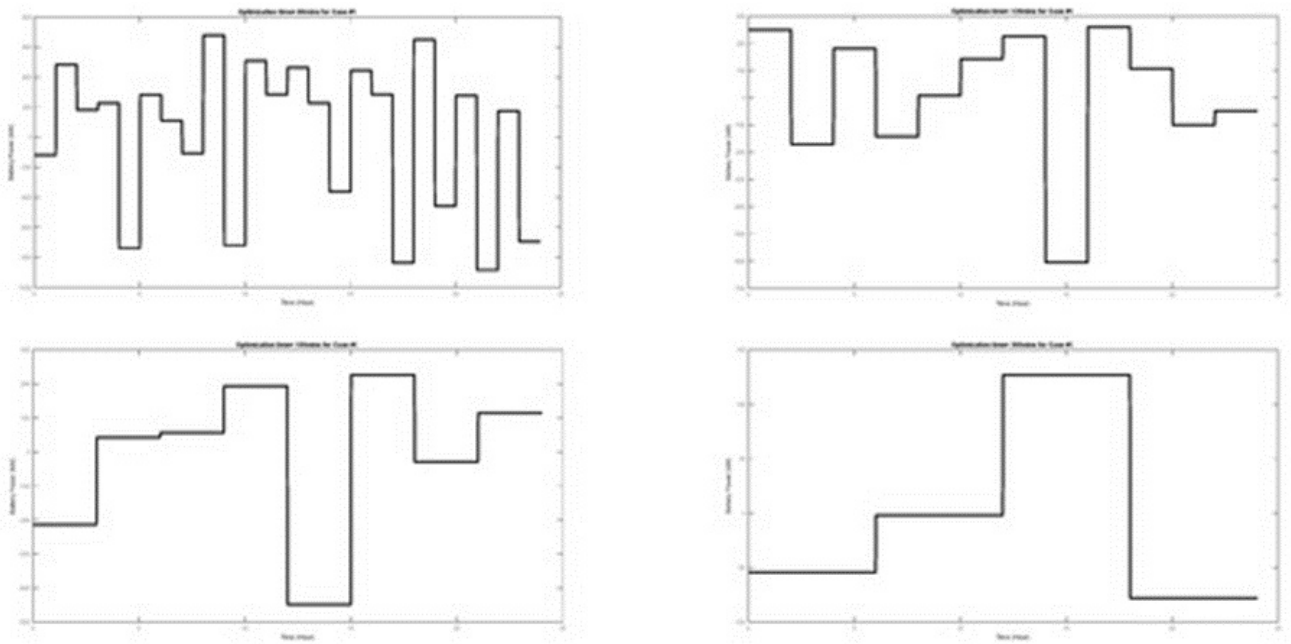


Figure 13. Battery power for different optimization times when Ppv prediction is almost correct (Case 1).

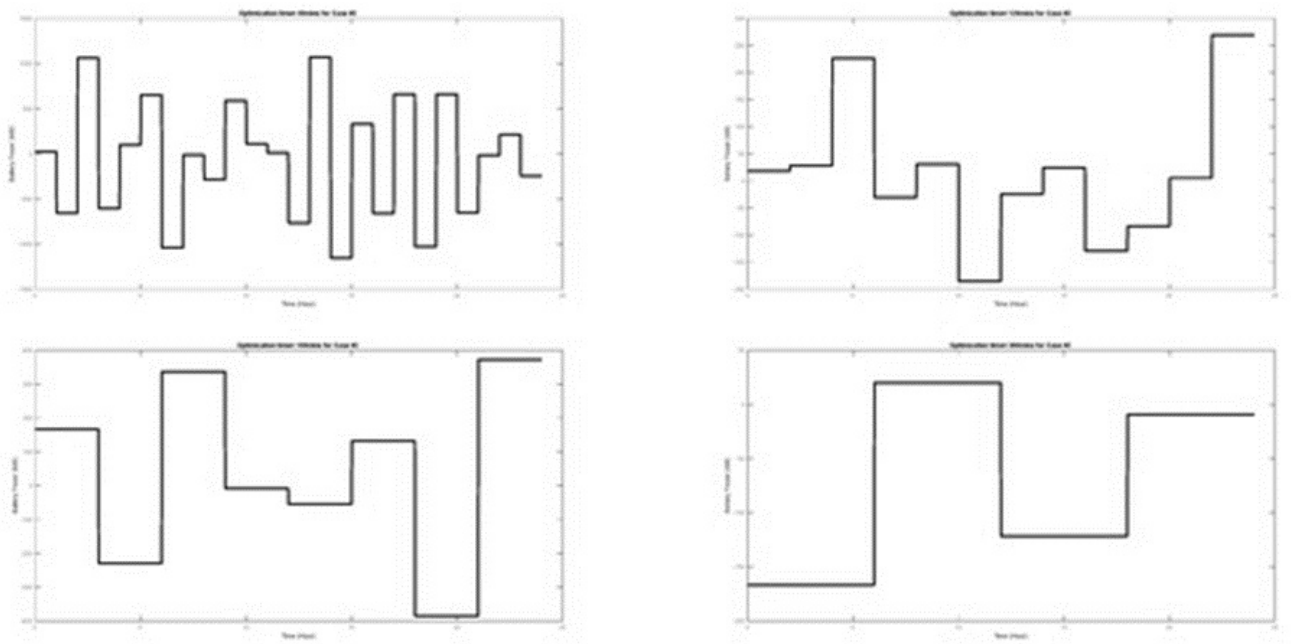


Figure 14. Battery power for different optimization times when Ppv prediction is not correct, and the initial Ppv prediction is used (Case 2).

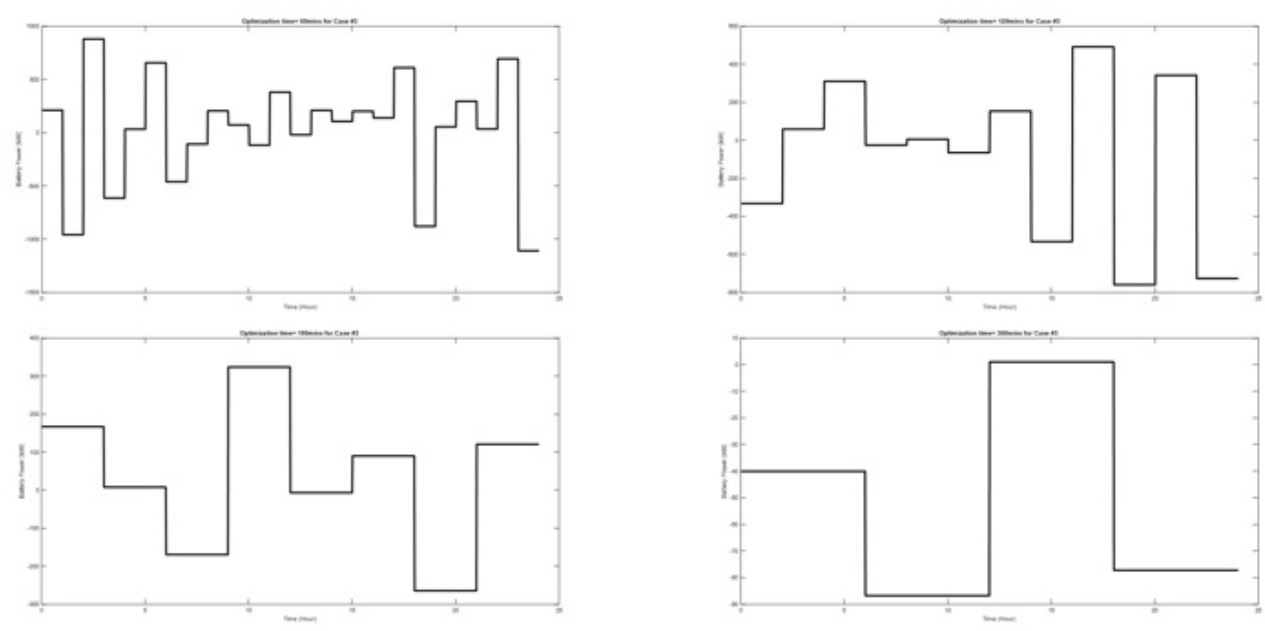


Figure 15. Battery power for different optimization times when Ppv prediction is not correct and updated Ppv prediction is used (Case 3).

Longer optimization time steps lead to shorter execution times. However, as shown in [Table 5](#), no uniform or predictable relationship exists between the optimization time step and the objective function (f_{obj}). While Case 1 shows that increasing the time step reduces f_{obj} , this pattern does not hold for Cases 2 and 3. Notably, the lowest f_{obj} value occurs at an optimization time step of 180 minutes, reinforcing the importance of carefully tuning the optimization interval.

Table 5. Simulation result for different optimization times.

Case #	Optimization time step (Min)	f_{obj}	Execution time (s)
1	60	908.3254	1407.4782
	120	878.2173	624.8655
	180	838.1195	412.1138
	360	772.5345	179.6685
2	60	1004.5173	1357.2318
	120	940.4602	568.5837
	180	817.5045	376.1011
	360	882.9894	153.232
3	60	809.2109	2738.9725
	120	842.6315	560.1691
	180	692.7327	368.921
	360	868.8008	239.0841

The optimization procedure determines the decision variables over the prediction horizon T_{pred} by employing MATLAB functions such as “solve,” assuming that these variables remain unchanged throughout the plateau duration $T_{plateau}$. The entire optimization routine is executed repeatedly at intervals defined by the optimization time T_{opt} . T_{pred} is treated as a dynamic parameter corresponding to the remaining hours of the day. The hyperparameters $T_{plateau}$ and T_{opt} are fine-tuned using the MATLAB “bayesopt” function.

Simulation outcomes reveal a marked improvement, with the smart EMS yielding a reduction of more than 50% in the objective function compared to the conventional EMS. This considerable gain confirms the effectiveness of the proposed method in reducing grid electricity costs while simultaneously maximizing the battery state of charge (SOC) at the end of the day. Moreover, the smart EMS exhibits strong robustness, delivering stable performance despite fluctuations in load power and solar irradiance, demonstrating its resilience against varying environmental conditions.

Furthermore, when partial shading conditions are introduced, the objective function experiences only a minor rise of 0.35553%. This limited impact illustrates the smart EMS’s high adaptability to natural disturbances, a critical attribute for maintaining dependable energy management under unpredictable conditions.

In addition, the simulation findings highlight the substantial influence of refreshing PV power forecasts on the objective function value. Aligning predictions with actual conditions is essential for achieving optimal outcomes. Likewise, the careful selection of the optimization time step is shown to affect both the resulting objective function value and the computational runtime, underscoring the importance of precise hyperparameter tuning.

Table 6 presents a comparative analysis between the present study and three closely related publications in the domain of greenhouse energy optimization and management. This side-by-side evaluation highlights the distinct strengths of the current work, particularly the substantial reduction in the objective function achieved through the smart EMS and its superior adaptability to environmental variations.

Table 6. A comparison between this paper and three other similar articles.

Metric	Current paper	Ziapour and Hashtroudi [32]	Adetoro et al. [33]	Adesanya et al. [34]
Objective function improvement (%)	> 50%	30%	40%	25%
Adaptability to environmental factors	High	Moderate	Low	Moderate
Simulation platform	Simulink/MATLAB	Energy-Plus	HOMER	TRNSYS
Decision variables	Network Power, Battery Power, Battery Energy	HVAC Power, Battery Capacity	Solar Power, Battery Energy	Heating Power, Storage Level
Optimization approach	Modified Multi-Objective Ellipse Optimization Method	GA	PSO	Linear Programming
Hyperparameters	Plateau Time, Prediction Time, Optimization Time	Crossover Rate, Mutation Rate	Swarm Size, Inertia Weight	Time Step, Convergence Limit
Simulation robustness	Confirmed under varying conditions (partial shading, load variations)	Not explicitly addressed	Limited validation under different conditions	Limited validation under different conditions

Overall, the simulation results strongly support the effectiveness of the proposed smart EMS in enhancing energy utilization within greenhouse settings. Its proven robustness, flexibility in the face of environmental changes, and sensitivity to parameter tuning collectively affirm the practical value of the smart EMS for real-world deployment, paving the way for more efficient and environmentally sustainable energy practices in agriculture.

Conclusion

In summary, this study addresses a critical aspect of energy management in agricultural greenhouses (GHs) by presenting an integrated solution that combines renewable energy sources (RESs) with an advanced smart energy management system (EMS). As global food demand continues to rise, the transition to more sustainable, resource-efficient greenhouse farming has become increasingly urgent. The developed multi-objective optimization framework—focused on simultaneously minimizing grid energy usage and maximizing battery state of charge (SOC)—marks a meaningful step forward. By prioritizing solar energy as the primary renewable energy source and implementing a smart EMS, the research effectively addresses both the economic burden of high operational costs and the ecological consequences of reliance on conventional power sources.

Beyond its theoretical contributions, this work delivers practical advantages for greenhouse operators and supports broader environmental goals. The key hyperparameters, refined through the ellipse optimization technique, significantly enhance the smart EMS's adaptability and overall performance. Comparisons against conventional optimization methods further validate the superior efficiency of the proposed smart EMS, reinforcing its capacity to transform energy management practices in greenhouse agriculture.

As the agriculture sector confronts the pressing need for sustainability, the findings of this study encourage the wider adoption of innovative, environmentally friendly technologies, laying the foundation for more resilient and efficient greenhouse operations in the future.

Potential directions for future work include exploring more sophisticated optimization algorithms to enhance the smart EMS's capabilities further. Expanding the system to incorporate additional renewable sources—such as wind or geothermal energy—also warrants investigation. Moreover, conducting field trials in real-world greenhouses to verify the proposed approach's performance under actual greenhouse conditions would provide valuable insights. Such efforts would build upon existing initiatives to refine energy management strategies and promote greater sustainability across the agricultural sector.

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Conflict of interest

None

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Ethics statement

None

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