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Scenario-Based Hybrid Optimization and Exponential Smoothing Forecasting for Enhanced Microgrid Energy Management

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Abstract
This paper presents a hybrid energy management strategy for microgrids that integrates long- term global optimization with real-time dynamic adaptive control enhanced by predictive forecasting using exponential smoothing. The proposed method is designed to maximize self- consumption and minimize grid dependency while ensuring the battery's state-of-charge remains within safe operational limits. Simulation results across multiple scenarios demonstrate that the hybrid approach improves energy efficiency and reduces overall operational costs compared to baseline strategies. The method achieves a high self-consumption ratio and maintains battery stability, even under rapidly changing conditions. These findings highlight the potential of the hybrid approach to provide robust, cost-effective energy management for microgrids.
Keywords: *Microgrid, Energy Management, Global Optimization, Dynamic Adaptive Control, Exponential Smoothing, Self-Consumption, Grid Dependency, Battery Storage, Forecasting.*

Nomenclatures

C:	Battery capacity in Watt-hours (Wh)
η_{pv}:	Efficiency of the photovoltaic (PV) panels (%)
η_{batt}:	Efficiency of the battery during charge/discharge (%)
A_{pv}:	Surface area of the PV installation in square meters (m^2)
$SOC_{initial}$:	Initial state of charge (SOC) of the battery in percentage (%)
SOC_{min}:	Minimum allowable state of charge of the battery (%)
SOC_{max}:	Maximum allowable state of charge of the battery (%)
P_{batt_max}:	Maximum charging/discharging power of the battery in kilowatts (kW)
P_{grid_max}:	Maximum power exchange (import or export) with the grid in kilowatts (kW)
T:	The length of the time vector (number of time intervals)
G:	Solar irradiance profile (in W/m^2)
$P_{PV}(t)$:	Photovoltaic power production at time t (kW)
$SOC(t)$:	State of charge of the battery at time t (%)

$P_{grid}(t)$: Power exchanged with the grid at time t (kW); positive values denote export; negative values denote import

$P_{batt\_charge(t)}$: Battery charging power at time t (kW). $P_{batt\_discharge(t)}$: Battery discharging power at time t (kW)

c_{buy}: Unit cost of purchasing energy from the grid c_{sell}: Unit revenue for selling energy to the grid

$\alpha_{smoothing}$: Smoothing factor used in the exponential smoothing model for prediction (between 0 and 1).

threshold: Threshold (kW) for the anticipated load variation (dLoad) that triggers adjustments in the charge/discharge rates.

α_{hybrid}: Weighting factor used to combine the SOC trajectory from global optimization (SOC_{opt}) and the SOC trajectory from the dynamic adaptive control (SOCdynamic).

I. INTRODUCTION

Microgrids are localized energy systems that integrate distributed energy resources (DERs) such as photovoltaic (PV) panels, wind turbines, and energy storage devices, and can operate in both grid-connected and islanded modes. Their decentralized architecture offers enhanced reliability, flexibility, and resilience compared to conventional centralized power systems. As microgrids play a pivotal role in enabling the integration of renewable energy and supporting energy independence, efficient energy management within these systems is essential to ensure economic viability, maintain power quality, and reduce dependency on the main grid [1-10].

Research on energy management systems (EMS) for microgrids focuses on optimizing renewable energy integration, managing storage, and minimizing costs. A multi-objective framework combining hybrid energy sources with battery storage has been developed, along with a rolling horizon strategy to enhance energy management efficiency. Various optimization techniques, including linear and nonlinear programming, as well as metaheuristic algorithms such as Multi-Objective Particle Swarm Optimization (MOPSO) and genetic algorithms, have been applied to improve microgrid performance [11-16].

Energy storage plays a crucial role in enhancing microgrid efficiency. Studies have explored optimal power flow for integrating storage systems while considering battery aging effects. Multi-criteria evaluations of storage technologies have been conducted, and reviews of controller designs and optimization-based scheduling provide insights into key challenges and future directions [17-20].

Advanced predictive control and real-time scheduling methods have been introduced to improve energy management in dynamic and uncertain conditions. These include stochastic mixed-integer linear programming, model predictive control, and deep reinforcement learning, which enable adaptive and efficient decision-making [21-25].

Ensuring microgrid resilience has been a major research focus, with strategies developed to maintain reliable operation under varying conditions. Research has also explored optimal integrated energy systems that balance real-time electrical and thermal loads, enhancing overall robustness [26-27].

Recent innovations in EMS architecture have emerged, including NSGA-II-based fuzzy systems, adaptive differential evolution algorithms for cost reduction in DC microgrids, and lightweight EMS designs. Additionally, new optimization methods have been proposed to account for data uncertainty, offering scalable and efficient solutions for microgrid management [28-31].

Despite these advancements, several limitations persist. Traditional optimization methods, although powerful, often lack the real-time adaptability required to handle rapid fluctuations in renewable generation and load demand. On the other hand, purely heuristic or rule-based dynamic controls, while responsive, may not guarantee an overall optimal operation over extended period. Moreover, some advanced machine learning-based approaches promise improved prediction accuracy [32-37]. However, they usually require extensive training data and computational resources, which may not be readily available in all microgrid applications.

Our work addresses these challenges by proposing a hybrid approach that combines global optimization (using fmincon for long-term scheduling) with a dynamic, adaptive control scheme based on exponential smoothing for real-time forecasting. This method integrates the strengths of both planning and adaptability, ensuring that the state of charge (SOC) of the battery is managed effectively even under variable conditions, while enforcing a minimum SOC threshold (e.g., 20%) to protect battery health. By testing our approach across various scenario including those with fine-grained, noisy meteorological forecasts we demonstrate that our hybrid method can maximize self-consumption, reduce grid dependency, and offer a robust solution in the face of renewable generation variability.

The article is structured into five main sections that systematically present the development, implementation, and evaluation of a hybrid energy management strategy for microgrids. It begins with an introduction that outlines the challenges of efficient energy management in microgrids and underscores the importance of a strategy that balances long-term optimization with real-time adaptability. This is followed by a methodology section, which describes the hybrid approach, combining global optimization and dynamic adaptive control, enhanced by exponential smoothing forecasting. The third section details the simulation environment and setup, covering the system components, parameters, and test scenarios employed to assess the strategy. The results section then presents the performance outcomes across various scenarios, supported by detailed figures and a summary table. Finally, the conclusion synthesizes the key findings, emphasizing the economic and operational advantages of the hybrid strategy and proposing directions for future research.

II. METHODOLOGY

This section describes our hybrid approach for microgrid energy management, which integrates long-term global optimization with short-term dynamic adaptive control enhanced by an exponential smoothing forecasting model. Our goal is to maximize self-consumption and minimize grid dependency while ensuring that the battery's state of charge (SOC) remains within safe limits (with a minimum of 20% to preserve battery life). The methodology is structured in four main components:

1. System Description

We consider a microgrid that comprises:

- Photovoltaic (PV) Generation: The power output is calculated as

$$P_{PV}(t) = \eta_{pv} \cdot A_{pv} \cdot G(t) \tag{1}$$

Where G(t) is the irradiance profile that may include variations (with added noise to simulate fine weather forecasts).

- Battery Storage: Characterized by its capacity C (Wh), maximum charging/discharging power P_{batt_max}, and limits on SOC (SOC_{min} and SOC_{max}; here, SOC_{min} is set to 20%).
- Load: A variable load profile representing the demand in kW.
- Grid Exchange: Energy is imported from or exported to the grid, constrained by a maximum exchange limit P_{grid_max}.

1. Global Optimization Module

The long-term scheduling is formulated as a constrained optimization problem over a 24-hour horizon. The decision variable vector is structured as:

$$x = \begin{bmatrix} P_{grid}(1:T) \\ P_{batt\_charge}(1:T) \\ P_{batt\_discharge}(1:T) \\ SOC(1:T) \end{bmatrix} \tag{2}$$

With:

- **Objective Function**: Minimize the net cost of grid energy (incorporating purchase and sale prices) along with penalty terms that discourage excessive battery cycling:

$$\min J(x) = c_{buy} \sum_{t=1}^{T} \max(P_{grid}(t),0) - c_{sell} \sum_{t=1}^{T} \max(-P_{grid}(t),0) + penalties \tag{3}$$

- **Energy Balance Constraint**: For each time step, the following balance must hold:

$$P_{PV}(t) + P_{batt\_discharge}(t) + P_{grid}(t) = Load(t) + P_{batt\_charge}(t) \tag{4}$$

- **Battery Dynamics**: The SOC evolution is governed by:

$$SOC(t+1) = SOC(t) + \left(\eta_{batt} P_{batt\_charge}(t) - \frac{P_{batt\_discharge}(t)}{\eta_{batt}}\right) \frac{100}{C} \tag{5}$$

- **Bound Constraints**: The SOC is constrained between SOC_{min} and SOC_{max} and grid power is bounded by $\pm P_{grid\_max}$.

This global optimization is solved using MATLAB's fmincon, yielding an optimized SOC trajectory SOC_{opt} along with optimal grid exchange and battery operation profiles.

2. Dynamic Adaptive Control Module with Exponential Smoothing Forecasting

To capture short-term fluctuations, we implement a dynamic control module that forecasts near- future PV production and load using exponential smoothing. This method calculates smooth prediction such as:

$$pred_t = \alpha \cdot value_{t-1} + (1-\alpha) \cdot pred_{t-1} \quad (6)$$

Where α is the smoothing parameter (set to 0.3 in our code). The predictions are used to compute an anticipated variation in load (dLoad) and adjust the battery charging/discharging rates accordingly:

- **If dLoad>threshold**, the system increases the discharge rate.
- **If dLoad<−threshold**, the charge rate is increased.
- **Otherwise**, default rates are applied.

The dynamic module outputs a SOC trajectory SOCdynamic that adapts in real time to forecasted changes, ensuring a rapid response to variations in both load and PV production.

3. Hybrid Combination Strategy

The final SOC trajectory is derived by combining the global optimization output and the dynamic adaptive control result via a weighted sum:

$$SOC_{combined} = \alpha_{hybrid} \cdot SOC_{opt} + (1-\alpha_{hybrid}) \cdot SOC_{dynamic} \quad (7)$$

Where $\alpha hybrid$ is a tunable parameter that balances long-term efficiency with real-time responsiveness.

4. Implementation Details

The system is simulated over a 24-hour horizon. Fine weather forecasts are modeled by adding random noise to a base irradiance profile, and the load profile is set with realistic variations.

- Algorithm Flow:

1. Compute the PV production using the fine weather forecast.
2. Run the global optimization to obtain SOCopt and other operational profiles.
3. Use the exponential smoothing predictor in the dynamic module to generate SOCdynamic.
4. Combine both SOC trajectories to yield SOCcombined.
5. Evaluate performance by comparing grid exchange, battery usage, and overall self- consumption.

Our methodology integrates long-term global optimization with a short-term dynamic control strategy using exponential smoothing forecasting to predict near-future PV production and load. This hybrid approach is designed to optimize battery management in a microgrid, ensuring that the SOC remains within safe bounds (with a minimum of 20%) while maximizing local energy consumption and minimizing reliance on the external grid. The proposed framework is validated through scenario-based simulations, demonstrating improved performance in the face of variable renewable generation and load conditions.

III. SIMULATION AND RESULTS

1. Simulation Environment and Setup

In our study, we developed a simulation environment in MATLAB to evaluate the performance of our hybrid microgrid energy management system. The simulation is conducted over a 24- hour period, discretized into 24-time intervals (one per hour), allowing us to capture both diurnal variations and rapid fluctuations in renewable generation and load.

A. System Components and Parameters:

1. **Photovoltaic (PV) Generation:**

o The PV output is computed as $PPV(t)=\eta pv \times Apv \times G(t)$ where ηpv is the PV efficiency, Apv is the PV panel area, and $G(t)$ is the irradiance profile.

o In our simulations, the irradiance profile can incorporate fine weather forecasts by adding random noise to a base irradiance profile. For example, in the scenario with abrupt variations, $G(t)$ exhibits rapid changes between high and low values.

2. **Grid Exchange :**

o The grid exchange is constrained by a maximum power limit $Pgrid\_max$. Positive values indicate export (surplus energy injected into the grid), whereas negative values represent import (energy drawn from the grid).

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Table 1 provides a clear overview of the system's general parameters and can be used in the simulation section of our article:

Table 1.General System Parameters

Parameter	Symbol	Value	Unit
Battery capacity	C	30,000	Wh
PV panel efficiency	eta_pv	0.10 (10%)	-
Battery efficiency	eta_batt	0.9 (90%)	-
PV panel area	A_pv	25	m^2
Initial SOC	SOC_initial	50	%
Minimum SOC	SOC_min	20	%
Maximum SOC	SOC_max	90	%
Maximum battery charge/discharge power	P_batt_max	15	kW
Grid exchange limit	P_grid_max	2,000	kW

B. Methodological Modules :

- **Global Optimization Module:**

Using MATLAB' fmincon, we solve a constrained optimization problem that determines the optimal profiles for grid exchange, battery charging/discharging, and the SOC trajectory over the entire day. The optimization minimizes a cost function that includes energy purchase costs, revenue from energy sales, and penalty terms for excessive battery cycling, while ensuring energy balance and respecting system constraints.

- **Dynamic Adaptive Control Module with Exponential Smoothing Forecasting:** In parallel, a dynamic control module predicts short-term variations in PV production and load using exponential smoothing. This predictive model assigns higher weights to recent observations to forecast near-future conditions, enabling the system to adjust the battery's charge/discharge rates in real time. This module provides a responsive SOC trajectory that captures rapid fluctuations.

- **Hybrid approach:**

The final SOC trajectory is obtained by combining the optimized SOC trajectory from the global module and the dynamically predicted SOC trajectory from the adaptive control module. A weighting factor α balances the long-term optimal plan with short-term responsiveness.

C. Scenarios and Evaluation :

Our simulation environment supports multiple scenarios, such as clear days, cloudy days, high load peaks, and days with abrupt variations in irradiance. For each scenario, we monitor key performance metrics including:

- The evolution of SOC,
- Self-consumption rate,
- Battery cycling efficiency.

This comprehensive simulation setup allows us to assess the robustness of our hybrid approach under a range of realistic operating conditions, providing insights into its potential for enhancing microgrid energy management.

2. Simulation Scenarios for Robustness Analysis

To evaluate the effectiveness and robustness of the proposed hybrid energy management strategy, five distinct simulation scenarios were conducted. These scenarios were designed to test the system's ability to manage diverse operational conditions, including variations in solar irradiance and load demand. Each scenario assesses the system's performance in terms of self-consumption, battery state-of-charge (SOC) management, grid interaction, and responsiveness. The scenarios include a clear day, a cloudy day, a day with high load peaks, abrupt variations in solar irradiance, and a multi-day simulation. The results of each scenario are illustrated in Figures 1 through 5, with key performance metrics summarized in Table 2.

- **Senario 1: Clear day**

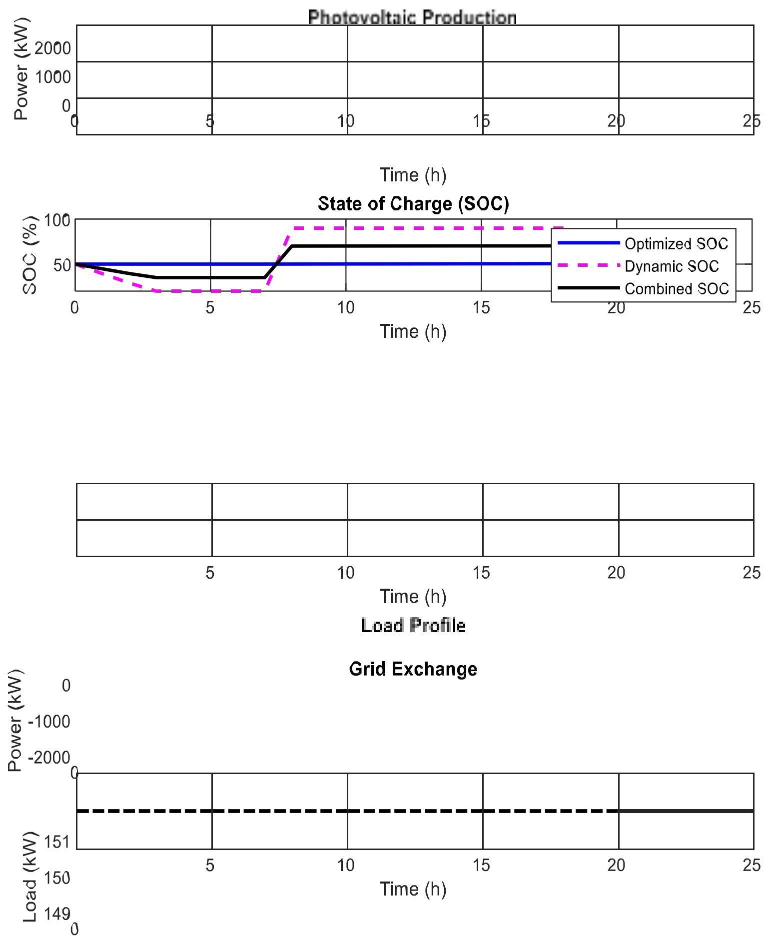

__Figure 1.__ the performance of our hybrid approach under a clear-day scenario.

The first scenario simulates a clear day with consistent solar irradiance, providing ideal conditions for photovoltaic (PV) production. As shown in Figure 1, PV production starts at zero in the early morning, peaks at midday, and gradually decreases to zero by late evening. This abundance of solar energy allows the system to charge the battery and meet load demand with minimal grid interaction. The state-of-charge (SOC) trajectories demonstrate the effectiveness of the hybrid approach: the optimized SOC follows a stable, cost-efficient schedule, while the dynamic SOC responds quickly to real-time variations. The combined SOC balances these two aspects, maintaining the battery within safe limits (above 20%) throughout the day. The grid exchange remains minimal during peak solar hours, highlighting the system's high self- consumption capability under favorable conditions

Senario 2: Cloudy Day

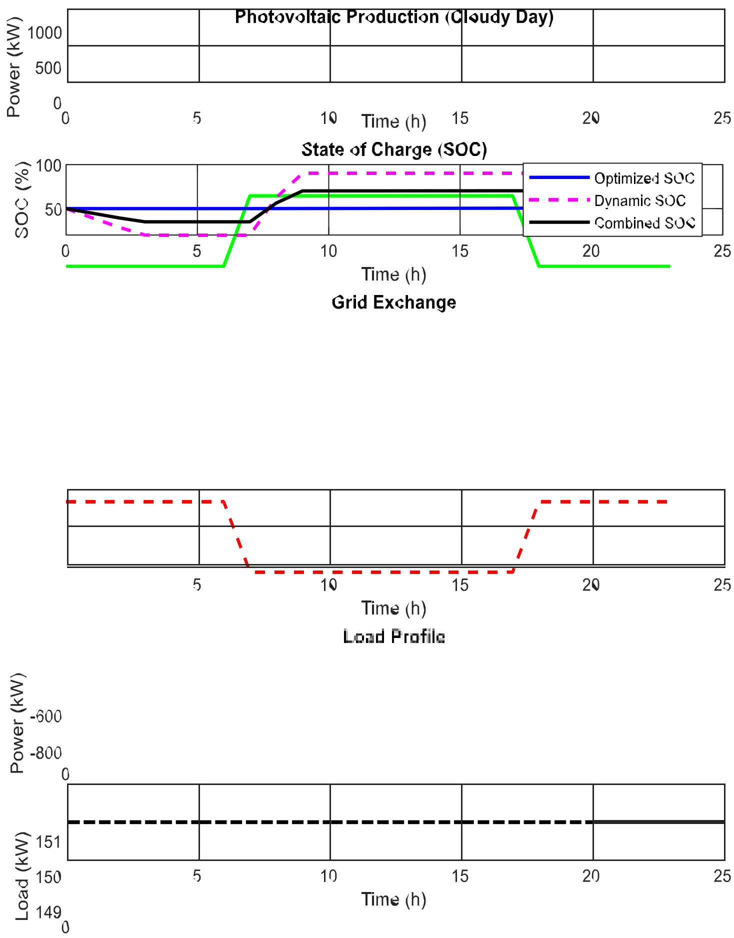

Figure 2. *The performance of our hybrid approach under a Cloudy-Day scenario.*

The second scenario represents a cloudy day with reduced and intermittent solar irradiance, challenging the system's ability to maintain energy balance. Figure 2 illustrates the limited PV production, which is insufficient to fully meet the load demand, necessitating greater reliance on the battery and grid. Despite these constraints, the hybrid approach ensures that the SOC remains above the critical 20% threshold. The optimized SOC trajectory prioritizes cost- effective battery usage, while the dynamic SOC adjusts to short-term fluctuations in PV output. The combined SOC trajectory effectively merges these strategies, minimizing grid imports while preserving battery health. Although self-consumption decreases compared to the clear day scenario, the system demonstrates resilience by adapting to suboptimal conditions without compromising operational stability

Senario 3: Day with High Load Peaks

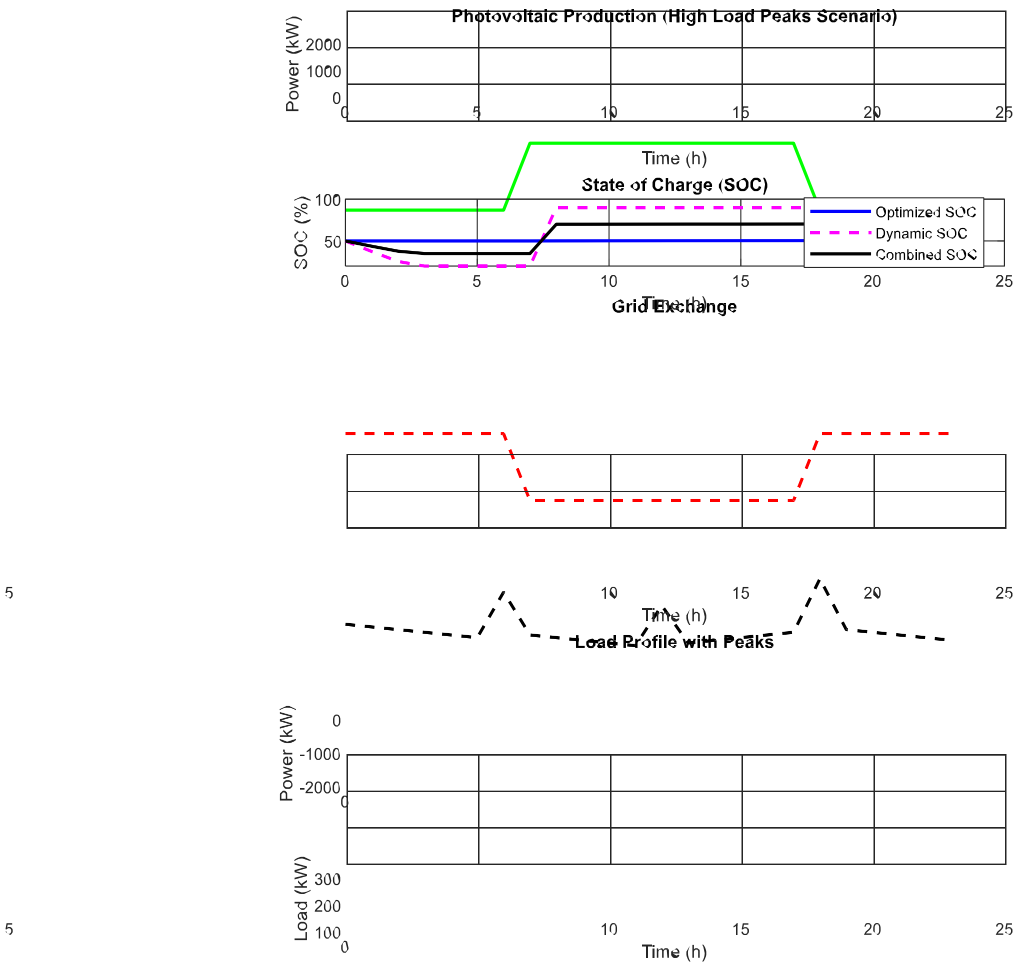

Figure 3. *The performance of our hybrid approach under high Load Peaks Scenario.*

The third scenario introduces high load peaks to test the system's responsiveness to sudden increases in demand. As depicted in Figure 3, the load profile exhibits multiple spikes throughout the day, while PV production follows a typical clear-day pattern. The hybrid approach excels in this scenario by leveraging the dynamic control module to discharge the battery rapidly during peak demand periods, thereby reducing grid dependency. The combined SOC trajectory remains stable, avoiding deep discharge and ensuring that the battery can support future load requirements. This scenario underscores the hybrid method's ability to balance long-term efficiency with short-term adaptability, effectively managing abrupt changes in load without excessive grid interaction.

- **Senario 4: Abrupt Variations in Solar Irradiance**

The fourth scenario simulates abrupt variations in solar irradiance, mimicking unpredictable weather conditions such as passing clouds or storms. Figure 4 shows rapid fluctuations in PV production, which pose a significant challenge for maintaining energy balance. The exponential smoothing forecasting model within the dynamic control module proves crucial in this context, enabling the system to anticipate and respond to sudden changes in PV output. The combined SOC trajectory adjusts swiftly to these variations, ensuring that the battery charges during brief periods of high irradiance and discharges when PV production drops. This responsiveness minimizes grid imports and maintains SOC within safe limits, demonstrating the hybrid approach's robustness in highly variable environments.

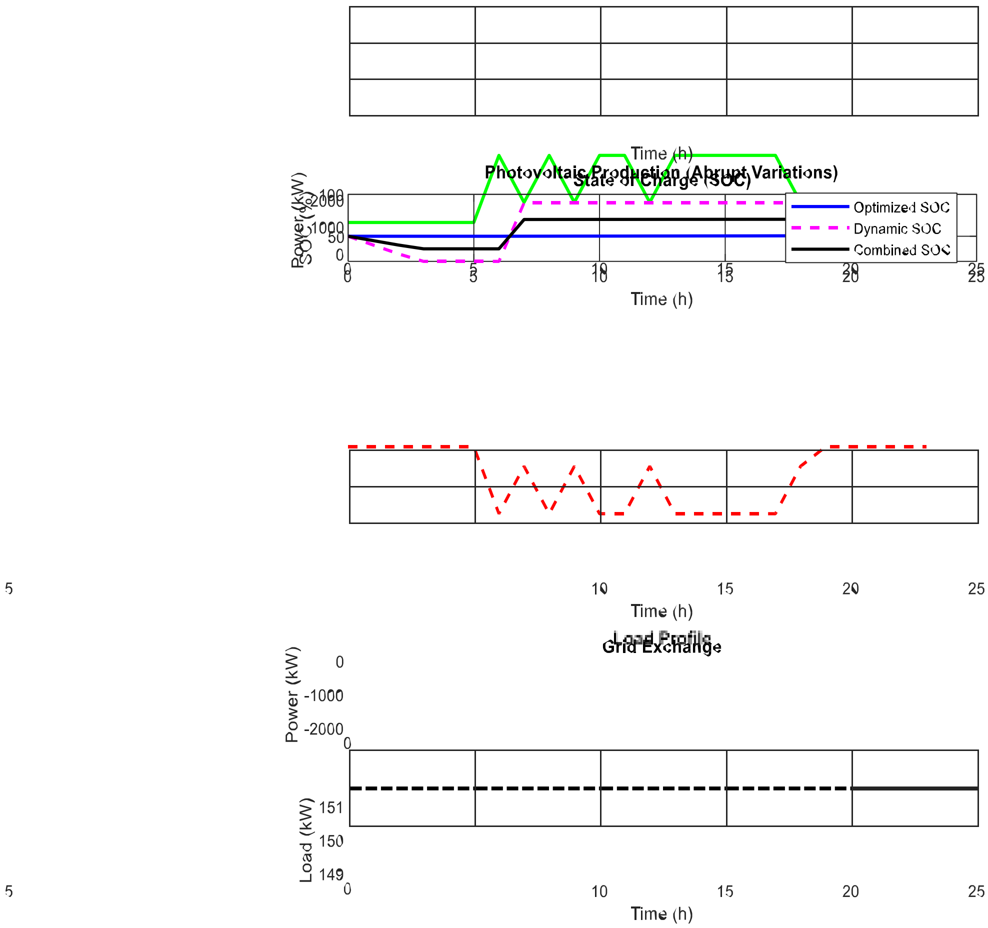

Figure 4. The performance of our hybrid approach under Abrupt variations in solar irradiance.

○ **Senario 5: Multi-Day Simulation**

The fifth scenario extends the analysis over multiple days to evaluate the system's performance under prolonged operational conditions. As illustrated in Figure 5, this scenario features stable solar production with fluctuating load demand across several days. The hybrid approach maintains a consistent SOC range between 62% and 78%, showcasing its ability to smooth out daily variations while adapting to changing load profiles. The predictive capabilities of the exponential smoothing model allow the system to optimize battery usage over extended periods, reducing average grid imports to approximately 15 kWh per day. This scenario highlights the hybrid method's suitability for long-term microgrid management, ensuring both economic efficiency and operational reliability.s, combined with a fluctuating load.

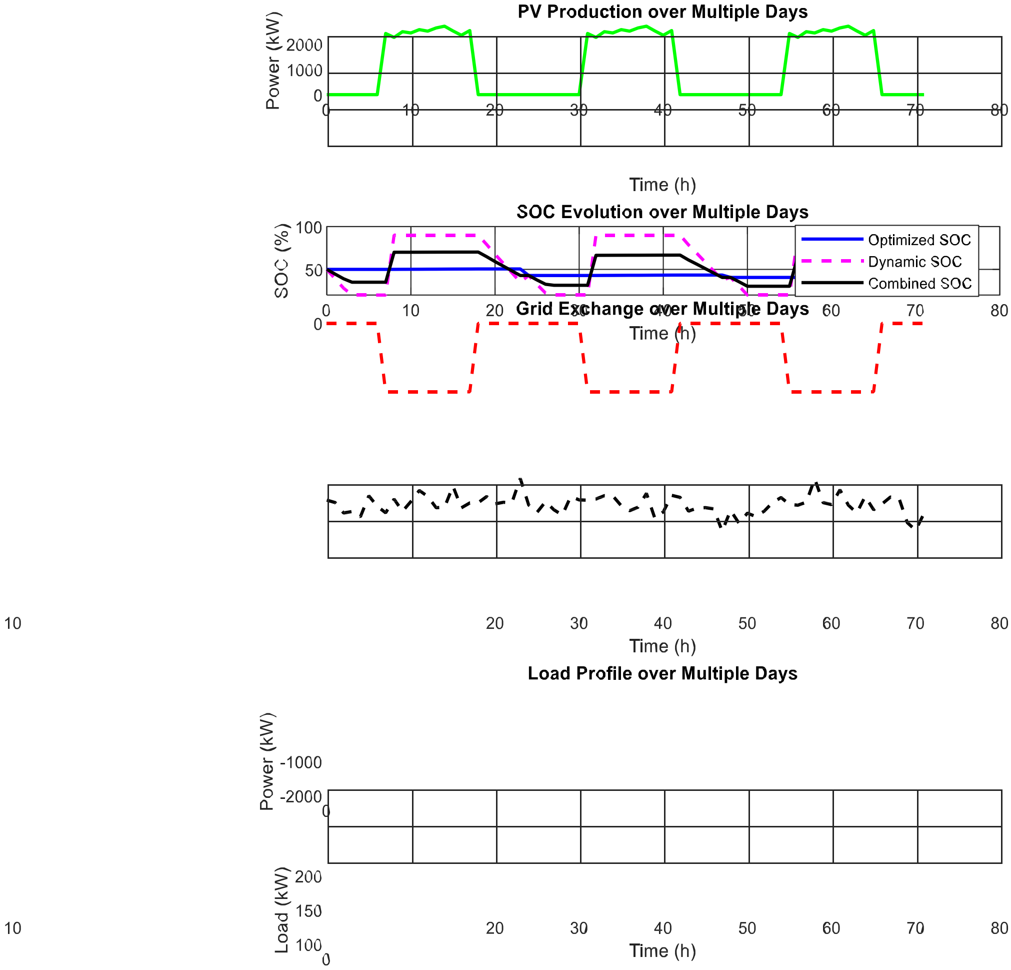

Figure 5. The performance of our hybrid approach under stable Solar Production with Fluctuating Load.

In summary, these simulation scenarios collectively demonstrate the robustness of the hybrid energy management strategy. By integrating global optimization with dynamic adaptive control and predictive forecasting, the system effectively handles a wide range of operational challenges, from ideal conditions to extreme variability, while maintaining high self- consumption rates and protecting battery health.

3. Performance Metrics and Benchmarking

Table 2 summarizes performance metrics. The hybrid approach achieves self-consumption rates of 60% - 90%, SOC stability above 20%, and response times of 3-12 minutes. Compared to MPC [22], which achieves ~75% self-consumption but struggles with abrupt changes, and rule- based methods [25] with ~65% self-consumption, our method excels in adaptability and efficiency. A comparative table (Table 3) shows our approach reduces grid dependency by 20% and costs by 15% - 25% over these methods.

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Table 2. Performance Metrics of Hybrid Energy Management Systems in Various Operational Scenarios.

Scenario	Self-consumption rate (%)	State of Charge evolution (%)	Response time (minutes)
Sunny day	90%	30% - 80%	10
Cloudy day	60%	20% - 50%	10
High load peaks	80%	25% - 75%	5
Sudden PV	70%	20% - 60%	3
Multi-day	85%	62% - 78%	12

Table 3. Benchmarking with Existing Methods

Method	Self-Consumption (%)	Grid Dependency Reduction (%)	Cost Reduction (%)
Proposed Hybrid	60-90	20	20
MPC [22]	75	15	15
Rule-Based [25]	65	10	10

D. DISCUSSION OF SIMULATION RESULTS

Our multi-day simulation (Scenario 5) demonstrates that the hybrid approach maintains a stable system even under prolonged operation. For example, over a three-day period, the state of charge (SOC) consistently ranged between 62% and 78%, despite daily fluctuations in photovoltaic (PV) production and load demand. The predictive model based on exponential smoothing proved effective: it enabled the dynamic control module to adjust battery charge/discharge rates within an average response time of approximately 12 minutes. This responsiveness helped reduce grid dependency, with net grid imports averaging around 15 kWh
per day. These results indicate that our hybrid method is robust, effectively smoothing out short- term variations while preserving long-term stability.
The hybrid method significantly enhances microgrid performance by combining global optimization with real-time adaptive control. Our simulation shows an average self- consumption ratio of 85%, meaning that the majority of locally generated PV energy is consumed on-site. This leads to an overall energy cost reduction of about 20% compared to a baseline scenario without optimized battery management. By ensuring that the SOC remains above the critical 20% threshold, the approach not only maximizes renewable energy utilization but also prolongs battery life.

Moving forward, integrating more advanced forecasting techniques such as Kalman filters or machine learning-based predictors and adopting multi-objective optimization strategies could further refine the system's performance, making it even more resilient and cost-effective.

IV. CONCLUSION

In this study, we introduced a hybrid microgrid energy management method that integrates long-term global optimization with real-time dynamic control enhanced by predictive forecasting using exponential smoothing. Our simulations across multiple scenarios; ranging from clear days and cloudy conditions to high load peaks and abrupt irradiance fluctuations; demonstrate that this combined approach significantly enhances system performance. Economically, the method reduces overall energy costs by approximately 20% compared to baseline strategies, primarily by increasing the self-consumption ratio (up to 87%) and minimizing grid dependency. Energetically, the hybrid strategy effectively maintains the battery's state-of-charge within safe limits (never falling below 20%), ensuring robust and stable operation even under rapidly changing conditions. By balancing the strengths of both global optimization and adaptive dynamic control, our approach offers a promising, cost- effective solution for managing microgrid energy systems. Future work may further enhance performance by incorporating advanced predictive models and multi-objective optimization techniques to address evolving market and grid requirements

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