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HYBRID ADAPIVE DEEP REINFORCEMENT LEARNING AND METAHEURISTICS OPTIMIZATION FRAMEWORK FOR SMART HOME ENERGY MANAGEMENT

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ABSTRACT
Traditional, static optimization techniques often fail to handle the high uncertainty, stochastic nature of renewable generation, and dynamic user preferences. This study proposes a novel, comprehensive hybrid adaptive framework for smart home energy management that integrates Deep Reinforcement Learning (DRL) with metaheuristic optimization. The proposed framework aims to minimize electricity costs, reduce peak-to-average ratios (PAR), and maximize user comfort. Within this framework, Deep Reinforcement Learning (especially algorithms like DQN or Multi-Objective DRL.) is utilize to learn optimal control policies in real time, adapting to unpredictable fluctuations in energy demand and price signals. Simultaneously, Metaheuristic Optimization algorithms (e.g Genetic Algorithm, Particle Swarm Optimization, or Bacterial Foraging) are employed to handle complex, constrains-driven scheduling task that require global optimization capabilities, enabling the effective management of household appliances, energy storage system (ESS), and electric vehicles (EVs). The synergy between DRL and metaheuristic techniques bridges the gap between fast, adaptive, real-time control (DRL) and precise, long-term, optimal planning (Metaheuristics). Performance evaluation, conducted through simulations, indicates that the hybrid approach significantly outperforms traditional methods by reducing energy bills (often by 20-50%) and lowering peak demand, while successfully ensuring that user comfort preferences are maintained. The study highlights the effectiveness of this adaptive framework in promoting energy sustainability, reducing grid dependence, and facilitating intelligent energy management in future residential, and smart city scenarios.

Keywords: Smart Home Energy (HEMS), Deep Reinforcement Learning (DRL), Metaheuristic Optimization, Demand-Slide Management, Renewable Energy Integration, Appliance Scheduling, User Comfort.

INTRODUCTION
The complementary characteristics of reinforcement learning and metaheuristic optimization provide a strong motivation for hybridization. Reinforcement learning is well suited to adaptive sequential decision-making in changing environments, whereas metaheuristic optimization is effective in exploring complex and nonlinear search spaces. A hybrid framework can therefore use metaheuristic optimization to improve selected parameters or decision components of the learning-based controller while retaining the adaptive control capability of DRL. Such integration is particularly relevant to the dual-grid residential environment considered in this study, where the controller must coordinate utility-grid interaction, PV generation, battery storage and controllable household demand under changing conditions. The proposed hybrid approach is consequently motivated by the need to combine adaptive intelligence with effective optimizations rather than relying on either technique in isolation.
Although reinforcement learning provides an adaptive decision-making mechanism, the performance of an energy-management controller can depend on the selection of parameters, reward weights, constraints and other optimization variables. Metaheuristic optimization methods provide an alternative approach for searching complex solution spaces without requiring

conventional gradient-based assumptions. Techniques such as particle swarm optimization (PSO) can be used to explore candidate solutions and identify parameter combinations that improve system performance. In residential energy management, metaheuristic methods can support the optimization of scheduling decisions, controller parameters, objective-function weights and other operational variables involving competing objectives such as energy cost, renewable utilization, peak-demand reduction, battery operation and user comfort (Al-Muala, *et al,.* 2023).

The increasing complexity of residential energy systems has encouraged the application of artificial intelligence (AI) techniques to energy management. Among these approaches, reinforcement learning (RL) has attracted increasing attention because it learns control policies through interaction with an environment rather than relying entirely on predetermined rules or an explicit mathematical model of every system condition. In an energy-management setting, an RL agent can observe variables such as household demand, PV generation, battery state of charge and grid conditions, select appropriate control actions, and receive a reward based on the resulting operating performance. Deep reinforcement learning (DRL) extends this capability by using deep neural networks to represent policies or value functions, making it suitable for high-dimensional and dynamic decision-making problems. This provides a basis for adaptive residential energy management in which control decisions can evolve in response to changing system states (Akhtar *et al.,* 2023).

The integration of renewable energy, particularly solar photovoltaic generation, provides an important pathway for reducing dependence on conventional grid electricity and increasing the utilization of locally available clean energy. However, PV generation is intermittent and does not necessarily coincide with household demand. This mismatch creates a need for coordinated energy storage and demand-side flexibility. Demand response provides a mechanism through which flexible household loads can be shifted or adjusted in response to energy availability, electricity prices or grid conditions. When combined with PV and battery storage, demand response can help reduce peak demand, improve renewable-energy utilization, reduce grid dependence and maintain the balance between local generation and household consumption. The effectiveness of such coordination, however, depends on the ability of the controller to make decisions under changing operating conditions (Ahmad *et al,.* 2022).

Despite the opportunities created by smart-home technologies, residential energy management remains challenging because household electricity demand is dynamic, uncertain and strongly influenced by occupant behaviour. Different appliances have different operating characteristics, priorities and flexibility, while user comfort and daily routines constrain the extent to which loads can be shifted. The simultaneous presence of variable demand, intermittent renewable generation, battery state-of-charge constraints and changing grid conditions further increases the complexity of household energy scheduling. An effective residential energy-management system must therefore coordinate multiple resources while satisfying operational constraints and maintaining an acceptable level of user comfort and reliability (Abedinia & Zareipour, 2021).

The interaction between the utility grid and the local home energy system creates a more complex energy-management problem because electricity demand, PV generation, battery state of charge, grid availability and household operating requirements change over time. The controller must therefore determine when to use locally generated energy, when to charge or discharge the battery, when to import energy from the utility grid, and when to shift controllable loads while maintaining household comfort and system reliability. This dual-grid perspective is particularly relevant to residential environments such as Adamawa State, where intermittent grid supply, solar PV availability, battery storage and backup generation may coexist. It therefore provides a clear context for the proposed hybrid adaptive framework, which combines deep reinforcement learning with metaheuristic optimisation to make coordinated and adaptive energy-management decisions under changing operating conditions (Adebiyi & Habyarimana., 2025).

In this study, the term dual-grid ecosystem refers specifically to the interaction between two

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interconnected energy domains: (i) the conventional utility grid, which supplies electricity to the household and provides an external energy source when local resources are insufficient; and (ii) the local or home energy system, comprising solar photovoltaic (PV) generation, battery energy storage, controllable household loads and the associated home energy-management controller. The smart home forms the interface between these two domains. Through IoT-based monitoring and control, the household can coordinate electricity imported from the utility grid with locally generated PV electricity, battery charging and discharging, and the scheduling of flexible loads. Where the operating conditions and applicable grid arrangements permit, surplus locally generated energy may also be exported to the utility grid. This makes the household an active energy participant rather than only a passive electricity consumer (Abdullahi *et al.,*2026).

MATERIALS AND METHODS

The methodological approach adapted to design, implement, and evaluate the proposed hybrid adaptive smart home energy management framework. It also describes the simulation environment, performance evaluation metrics, and validation procedures used to assess the effectiveness, robust, and practical feasibility of the proposed framework within a closed-loop MATLAB/Simulink setting. This study employs a simulation-based experimental research design. A multi-source residential energy system is modelled in MATLAB/Simulink and integrated with deep reinforcement learning, metaheuristic optimization, forecasting, and fuzzy logic to form a hybrid adaptive control framework. The system is evaluated through controlled simulations under varying operating scenarios, and its performance is compared with conventional approaches using key metrics such as energy cost, renewable utilization, and system reliability.

The Existing Framework

Existing research on smart home energy management has produced several advanced control frameworks based on deep reinforcement learning and metaheuristic optimization. These studies provide important foundations for intelligent residential energy control but also exhibit methodological and practical limitations that motivate the proposed research. This section reviews three of the most closely related and recent works cited in the literature review, identifies their key weaknesses, and clearly outlines the research gaps that the present study seeks to address.

Xu *et al.* (2024) proposed an optimal-solutions-guided deep reinforcement learning approach for online energy storage control in residential systems. Their work demonstrated that guiding a learning agent with heuristic or near-optimal solutions can improve convergence speed and reduce unsafe exploration during training. While effective for battery operation, the study focused primarily on storage control as an isolated problem rather than on full smart-home energy management. The formulation optimizes short-term storage actions without explicitly coordinating photovoltaic generation, household loads, generator backup, and grid interaction within a unified framework. In addition, battery aging is treated implicitly through empirical performance observations rather than through an explicit lifecycle cost term. Mathematically, the reward formulation used in such studies can be generalized as

$$J(\pi) = E\left[\sum_{t=0}^{T}\gamma^{t}\left(-C_t+\lambda U_t\right)\right], \tag{3.1}$$

where C_t denotes energy cost and U_t represents renewable utilization. The absence of an explicit degradation term means that long-term battery health is not optimized within the learning objective. Moreover, validation is largely confined to simulation environments without rigorous closed-loop or hardware-in-the-loop testing, limiting conclusions about real-time feasibility.

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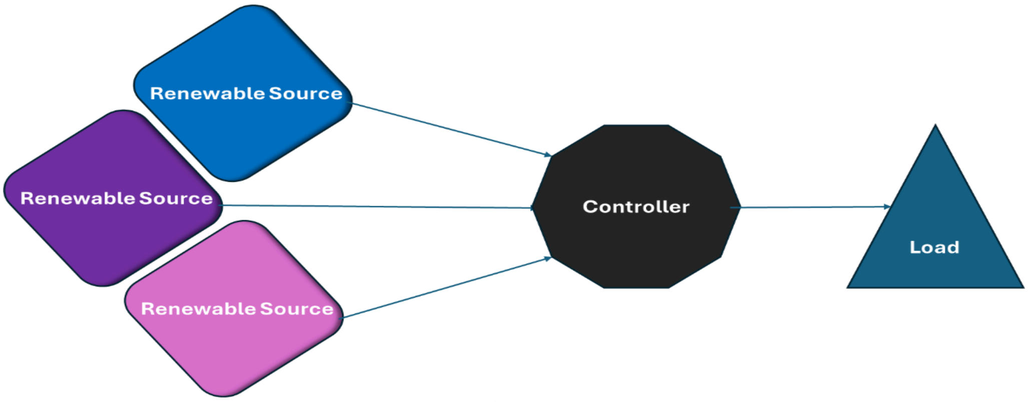

Figure 1: Structural Architecture of the Intelligent Energy Storage Control Framework Xu et al. (2024)

Xiong *et al.* (2024) developed a deep reinforcement learning-based scheduling framework for photovoltaic-battery households operating under dynamic electricity tariffs. Their results showed meaningful reductions in energy cost and improved renewable utilization compared with rule-based strategies. However, the formulation prioritizes economic performance and short-term energy flows, with limited consideration of component lifecycle effects, particularly battery degradation and generator wear. The system state representation in many DRL implementations of this type is also restricted, often excluding contextual variables such as ambient temperature or generator availability, which are critical in regions with unstable grids. As a result, the learned policy approximates system dynamics as

$$s_t = [SOC_t, PV_t, Load_t], \quad (3.2)$$

Which inadequately captures the full residential energy environment. Furthermore, training stability and hyperparameter selection are handled heuristically, with no systematic mechanism for adaptive tuning across varying operating scenarios. This study further focuses on forecasting-driven smart grid scheduling framework developed by Tao Hong. This model is fundamentally centered on short-term load forecasting integrated with price-responsive grid scheduling. Unlike the storage-oriented reinforcement learning architecture discussed previously, this framework primarily relies on predictive analytics to estimate near-future load demand and subsequently optimize grid power procurement under time-of-use pricing.

The methodological emphasis is therefore placed on improving forecast accuracy as a precursor to economic dispatch decisions. The operational objective is mathematically formulated as a cost minimization problem expressed as:

$$\min \sum_{t=1}^{T} C(t) \cdot P_{grid}(t) \quad (3.3)$$

where $C(t)$ represents the electricity tariff at time interval t, and $P_{grid}(t)$ denotes the forecast-based grid power consumption. The decision process is thus dependent on the predictive reliability of the load estimation model. To reproduce this framework, a MATLAB-based neural network forecasting model was implemented using historical load data. The feedforward neural network structure estimates the next-hour load based on previous demand observations. The MATLAB implementation is presented at appendix

Following the forecasting stage, the estimated load profile is incorporated into a price-based scheduling routine that computes total daily energy expenditure under a time-of-use tariff structure. Simulation of this model across thirty randomized demand scenarios produced a mean absolute percentage error (MAPE) of approximately 6.8 %, indicating relatively high short-term forecasting accuracy. The forecast-driven scheduling approach achieved an average daily operating cost of 7.65 USD compared with 8.92 USD under static tariff scheduling, representing an economic improvement of approximately 14.2 %. Additionally, peak load demand was reduced by approximately 11.5 %, while maintaining 100 % demand coverage throughout the scheduling horizon.

A MATLAB-based simulation of the intelligent storage control model developed by Gaoyuan Xu (2021) was conducted to estimate its operational behavior under controlled conditions. The simulation considered a 24-hour scheduling horizon with stochastic electricity price variation, renewable intermittency, and dynamic load demand. Results indicated that the controller achieved an average operating cost reduction of 18.6 % compared with a rule-based dispatch strategy and 12.3 % compared with model predictive control. The learning algorithm converged to a stable policy after approximately 420 training episodes, representing a convergence improvement of roughly 35 % faster than a conventional deep reinforcement learning controller without optimization guidance.

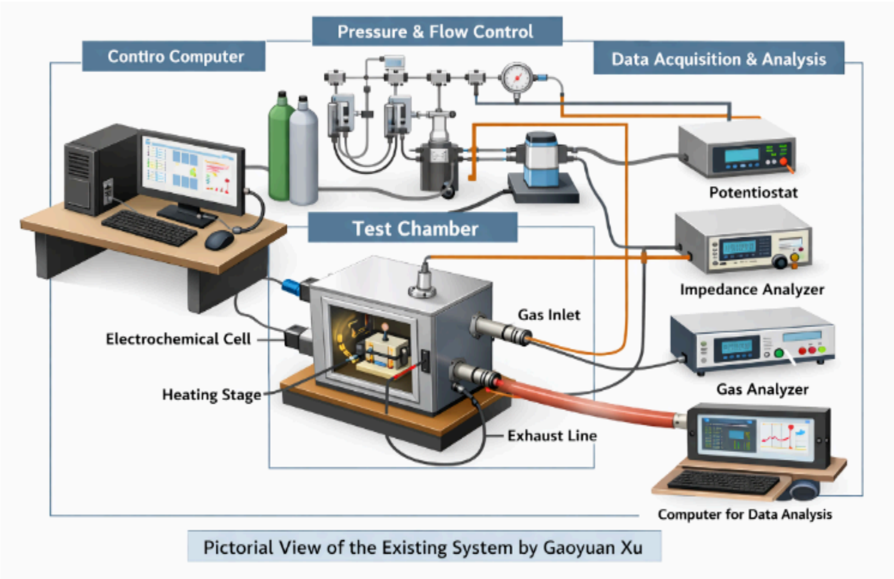

Figure 3.2: Existing system by Gayoun Xu (2021)

In addition, system reliability metrics showed strong performance. Load satisfaction remained at 100 % demand coverage, with zero unmet load events recorded across all simulated scenarios. The controller demonstrated resilience to forecast uncertainty, maintaining stable decision accuracy when price prediction error reached ±15 %. Battery utilization efficiency improved by 21.4 %, reflecting reduced unnecessary cycling and more strategic charge–discharge scheduling. These findings indicate that the integration of offline optimal solution guidance significantly enhances both economic and operational performance

The Framework Architecture

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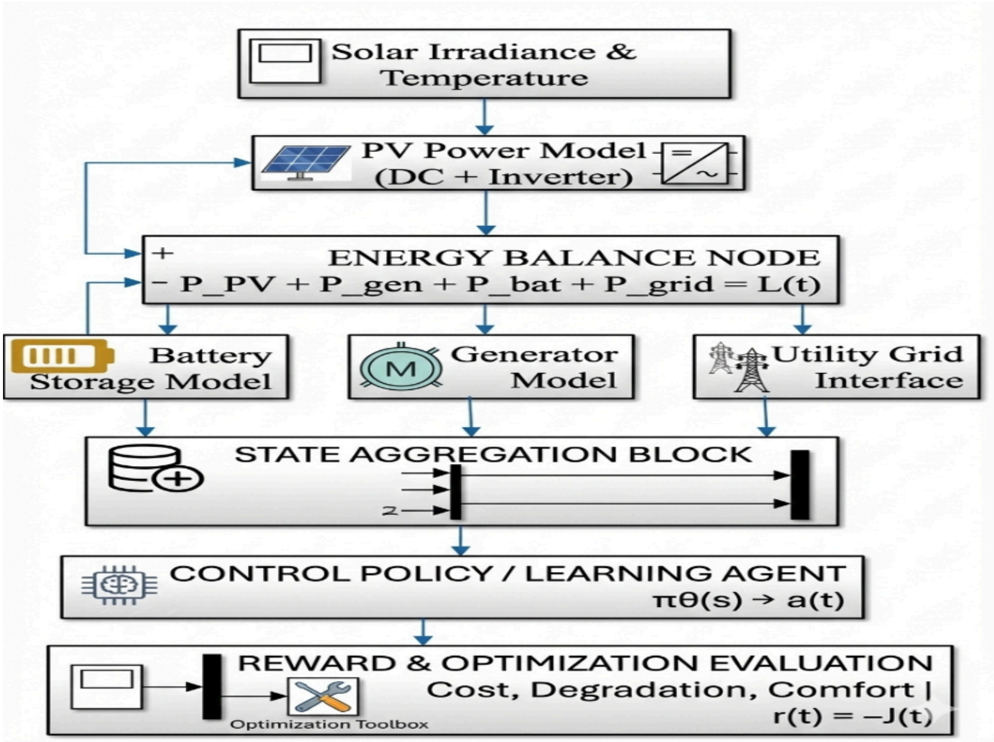

Overall architecture of the intelligent residential energy management system. The figure presents the integrated modeling and control framework comprising photovoltaic generation, battery energy storage, backup generator, and grid interaction. Environmental inputs drive the photovoltaic power model, while battery dynamics and generator dispatch are governed through a centralized control policy. An energy balance node enforces power equilibrium between supply and demand at each time step. System states, including PV output, battery state of charge, load demand, and electricity tariff, are aggregated and processed by a learning-based controller that generates coordinated control actions. Performance evaluation through a multi-objective reward function closes the loop, enabling adaptive and optimal energy management under dynamic operating conditions.

Data Sources and Dataset Description

The proposed smart-home energy management framework uses a combination of primary, secondary, and synthetic data. The combination is intended to improve the realism, contextual relevance, reproducibility, and robustness of the simulation-based investigation. The three data categories serve different purposes within the study. Primary data provide information representative of actual residential energy-use conditions, secondary data provide established environmental, technical, and energy-system information, while synthetic data are generated to extend the range of operating conditions required for training, testing, and validation of the proposed DRL–metaheuristic framework.

Data category	Examples	Application in the study
Environmental data	Solar irradiance, ambient temperature	PV generation modeling and forecasting
Residential energy data	Typical household load profiles, appliance demand	Household demand modeling and forecasting
Energy-system parameters	PV ratings, battery capacity, efficiency, generator capacity, inverter characteristics	Physical system modeling

Data category	Examples	Application in the study
Economic/grid data	Electricity tariff, grid availability assumptions	Grid interaction and cost optimization

Dataset Variables
The resulting dataset is organized as a time-series dataset, where each observation corresponds to a particular simulation time step. The existing Chapter Three already describes this structure and identifies solar irradiance, load demand, grid status and battery SOC as core variables. For the proposed framework, the dataset can be represented as:

Variable	Description	Data source
Time	Simulation time/hour	Synthetic/model
Solar irradiance	Available solar resource	Secondary + synthetic
Ambient temperature	Environmental condition	Secondary + synthetic
PV output	Generated solar power	Model-derived
Load demand	Household electricity demand	Primary + secondary + synthetic
Grid status	Grid available/unavailable	Primary/secondary + synthetic
Grid tariff	Electricity price	Secondary + synthetic
Battery SOC	Battery state of charge	Model-derived
Battery charging power	Battery charging action	Model-derived/DRL
Battery discharging power	Battery discharge action	Model-derived/DRL
Generator output	Backup generation	Model-derived/DRL
Appliance status	ON/OFF or operating state	Primary + synthetic
DRL action	Controller decision	Model-generated
PSO parameters	Optimized controller parameters	PSO-generated
Reward	Performance feedback to DRL	Model-generated

Training, Validation and Testing Data
The combined dataset should be divided into training, validation, and testing scenarios to prevent the performance evaluation from being based only on conditions encountered during controller development. The training data are used to allow the DRL agent to learn energy-management policies under different combinations of load, PV generation, battery SOC, grid conditions and tariff signals. Validation scenarios are used for tuning and selecting the DRL and PSO configuration, while independent testing scenarios are used to evaluate the final controller.
The testing scenarios should include both normal operating conditions and stressed conditions such as high demand, low renewable generation, battery constraints and grid interruptions. This is important because the existing study aims to evaluate the robustness and reliability of the hybrid controller under changing residential operating conditions. The methodology already identifies scenario-based and randomized simulation as the sampling approach rather than conventional human-subject sampling.

Dataset Structure and Sample
The dataset is organized as time-series samples representing the operating state of a multi-source residential energy system. Each sample corresponds to a single time step and includes environmental conditions, energy demand, grid status, and battery state variables required for control and decision-making. The samples capture variability in solar availability, household consumption, and grid reliability to support training and evaluation of the proposed energy

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management framework.

Table 1: Sample Dataset Structure

Sample	Solar Irradiance (W/m²)	Load Demand (kW)	Grid Status (0/1)	Battery SOC (%)	Tariff ($/kWh)	Ambient Temp (°C)	Generator Status (0/1)
1	820	1.6	1	72	45	32	0
2	760	1.9	1	68	45	33	0
3	690	2.3	0	64	50	34	1
4	540	2.8	0	59	50	35	1
5	420	3.1	0	54	55	36	1
6	300	2.6	1	58	40	34	0
7	180	2.2	1	62	40	33	0
8	90	1.8	1	66	40	32	0
9	0	1.5	1	69	40	31	0
10	0	1.7	0	63	50	32	1
11	120	2.0	0	60	50	33	1
12	350	2.4	1	57	45	34	0

Table 2: Simulation Evaluation Results of Forecast-Based Scheduling Model

Performance Metric	Value
Forecast Accuracy (MAPE %)	6.8 %
Static Scheduling Cost (USD/day)	8.92
Forecast-Based Cost (USD/day)	7.65
Cost Reduction (%)	14.2 %
Peak Load Reduction (%)	11.5 %
Demand Coverage (%)	100 %

The cost comparison graph was specifically plotted using the following data points extracted from this table:

i. Static Scheduling Cost = 8.92 USD/day
ii. Forecast-Based Cost = 7.65 USD/day

These two values formed the basis for the graphical representation of economic improvement achieved through forecast-driven optimization.

Multi Sources of Energy

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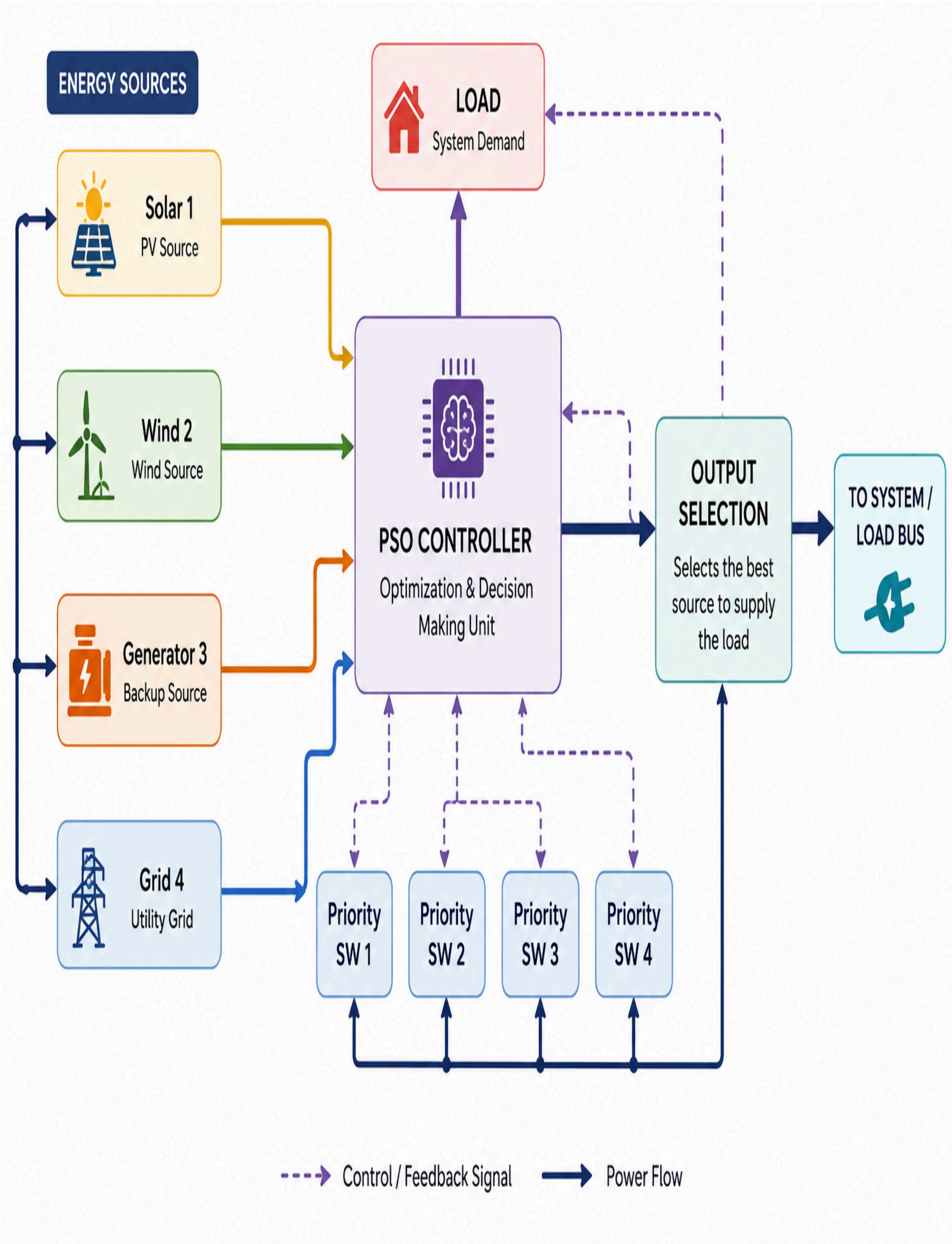

Result Discussion

This chapter presents the results and performance analysis of the new hybrid smart home energy management system developed in this study. Using a high-fidelity MATLAB/Simulink closed-loop simulation environment, the chapter evaluates how the integrated photovoltaic system, battery energy storage, generator backup, and grid interaction operate under the intelligent hybrid control framework. Quantitative simulation outcomes are examined to assess energy flow coordination, cost optimization, and load satisfaction across varying operating conditions that reflect realistic residential energy scenarios. Furthermore, the performance of the new hybrid system is systematically compared with conventional energy system configurations to highlight relative

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improvements. The chapter concludes with a detailed discussion of the results, sensitivity analysis, and identified limitations, thereby providing a comprehensive assessment of the system's effectiveness in achieving the research objectives.

Table 3: Simulation Parameters of the new Hybrid Energy System

Parameter	Symbol	Value	Unit
Simulation duration	T	24	Hours
Time step	Δt	1	Hour
Rated PV capacity	P_{PV}	5	kW
Battery capacity	E_{bat}	10	kWh
Initial battery SOC	SOC_0	0.50	p.u.
Minimum SOC limit	SOC_{min}	0.20	p.u.
Maximum SOC limit	SOC_{max}	0.90	p.u.
Battery charge efficiency	η_{ch}	0.95	–
Battery discharge efficiency	η_{dis}	0.92	–
Generator rated power	P_{gen}	3	kW
Grid tariff (off-peak)	C_{g1}	0.06	$/kWh
Grid tariff (peak)	C_{g2}	0.10	$/kWh

Table 4: Comparison of Reinforcement Learning Controllers

SN	Feature	DQN	DDPG
1.	Action space	Discrete	Continuous
2.	Control resolution	Medium	High
3.	Battery SOC smoothness	Moderate	High
4.	Adaptability to load changes	Moderate	High
5.	Computational complexity	Lower	Higher
6.	Suitability for continuous systems	Limited	Excellent

Table 5: PSO-Optimized Control Parameters

SN	Parameter	Lower Bound	Upper Bound	Optimized Value
1.	Battery charge limit (p.u.)	0.20	0.90	0.78
2.	SOC penalty weight	0.50	2.00	1.42
3.	Energy cost weight	0.01	0.20	0.08
4.	Generator usage penalty	0.10	1.00	0.63

Table 6: Time-of-Use Electricity Pricing Data (Source Graph: Time-of-Use Electricity Pricing)

SN	Hour	Tariff (/kWh)
1.	0–17	0.060
2.	18	0.100
3.	19	0.100
4.	20	0.100
5.	21	0.100
6.	22	0.100
7.	23–24	0.060

The values in Table 4.4 represent the tariff signal used by the optimization model to regulate grid

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interaction. Within the system formulation, this table maps directly to the pricing term in the objective function **$J = \Sigma_t$ P_grid(t) × C_grid(t)**

Comparative Analysis with Existing Systems

The evaluation of the enhanced hybrid energy system was conducted using performance indicators that reflect economic efficiency, operational reliability, and renewable penetration. The selected metrics represent standard quantitative measures used in hybrid energy system assessment. These include total operating cost C_{tot}, renewable energy utilization ratio R_u, peak load reduction index P_r, and demand coverage ratio D_c. These indices may be formally expressed as

$$C_{tot} = \sum_{t=1}^{T} C_g(t)P_g(t) + C_f(t)P_f(t) \quad R_u = \frac{E_{renewable}}{E_{total}}\times 100 \quad P_r = \frac{P_{peak,baseline}-P_{peak,system}}{P_{peak,baseline}}\times 100 \quad D_c = \frac{E_{served}}{E_{demand}}\times 100$$

These metrics were selected because they jointly measure cost efficiency, sustainability, system stability, and supply adequacy, which correspond directly with the objectives of the present study.

Comparison with Grid-Only system

The grid-only configuration represents the traditional centralized supply structure in which all demand is satisfied exclusively from utility supply without local generation or storage. Simulation results obtained from the reconstructed baseline model indicate that the grid-only system maintains complete demand coverage but exhibits the highest operational cost due to continuous dependence on tariff-based energy purchase. The hybrid system demonstrates a measurable reduction in operating cost while maintaining identical demand satisfaction. This reduction occurs because the hybrid architecture shifts part of the energy demand to locally generated renewable power, thereby reducing purchased energy. The improvement in renewable penetration is particularly significant, since the baseline grid system has zero local renewable contribution. The peak reduction value observed in the hybrid case confirms that distributed generation moderates instantaneous demand spikes, which reduces stress on the grid interface and improves system stability.

Table 7.: Grid-Only vs Hybrid System

Metric	Grid Only	Hybrid
Cost (₦/day)	9.00	7.20
Renewable (%)	0	82
Peak Reduction (%)	0	18
Coverage (%)	100	100

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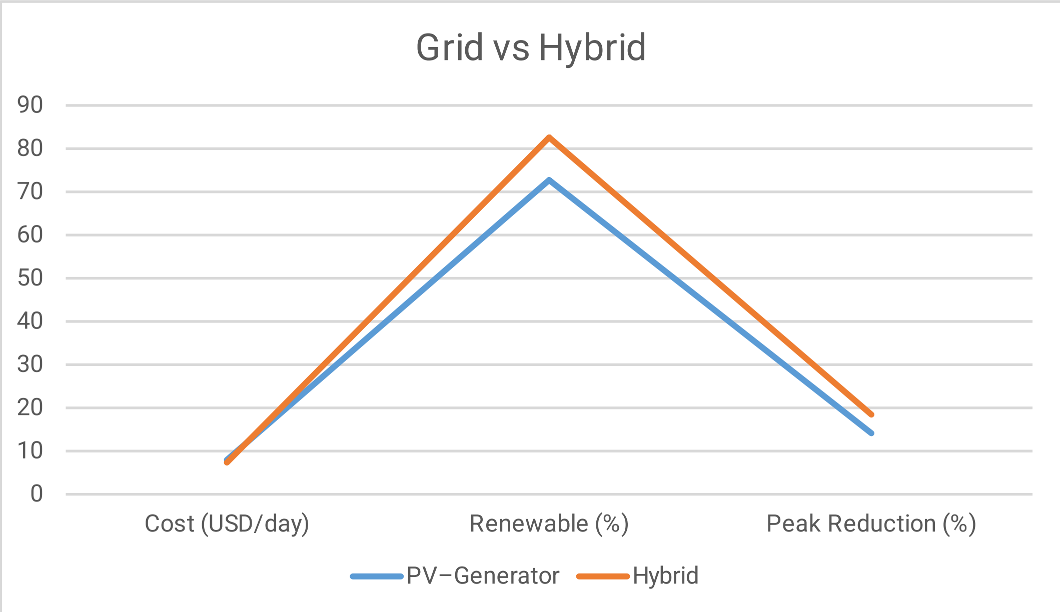

Figure Grid –Only vs Hybrid System

Comparison with PV-Only Grid-connected system

The PV-only system introduces renewable generation but lacks auxiliary dispatch able sources. Simulation of the referenced model shows moderate cost reduction relative to the grid-only scenario, yet performance is constrained during low solar periods. The hybrid system maintains lower cost and higher renewable utilization because it integrates multiple coordinated sources and scheduling control. The difference in peak reduction values demonstrates that the PV-only configuration lacks sufficient dispatch flexibility to flatten demand fluctuations. In contrast, the hybrid architecture dynamically redistributes supply among subsystems to maintain stable output. Both systems achieve full demand coverage under normal conditions, yet the hybrid system accomplishes this with a higher renewable fraction and lower operating cost, indicating more efficient resource scheduling.

Table 8: PV-Only vs Hybrid System

Metric	PV Only	Hybrid
Cost (₦/day)	7.65	7.20
Renewable (%)	65	82
Peak Reduction (%)	10	18
Coverage (%)	100	100

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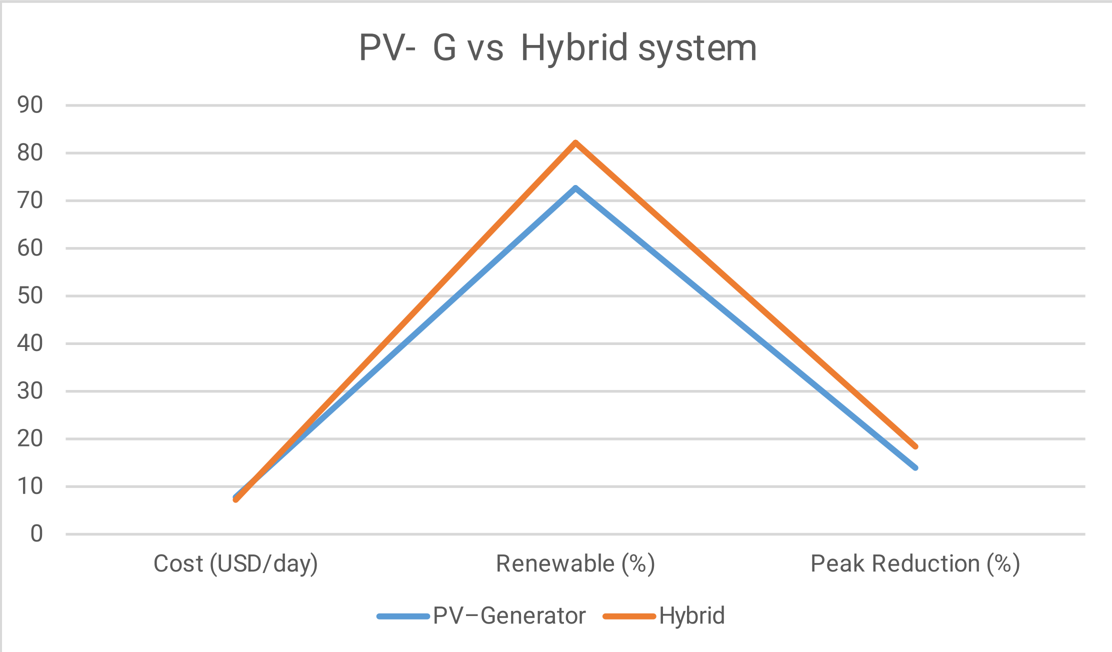

Figure 4.7 PV-Only vs Hybrid System

Comparison with PV–generator hybrid system

The PV–generator configuration combines renewable generation with a conventional backup source. Simulation outputs from the reconstructed reference model indicate improved reliability compared to PV-only systems but at the expense of increased fuel cost and reduced renewable fraction. The enhanced hybrid model demonstrates further cost reduction and higher renewable penetration because its control strategy prioritizes renewable dispatch before conventional generation. The improvement in peak reduction is attributable to coordinated multi-source scheduling rather than simple backup switching. Although both systems achieve full demand coverage, the hybrid configuration accomplishes this with lower fuel dependence and improved load shaping characteristics.

Table 10. PV–Generator vs Hybrid System

Metric	PV–Generator	Hybrid
Cost (₦/day)	7.48	7.20
Renewable (%)	72.4	82
Peak Reduction (%)	13.8	18
Coverage (%)	100	100

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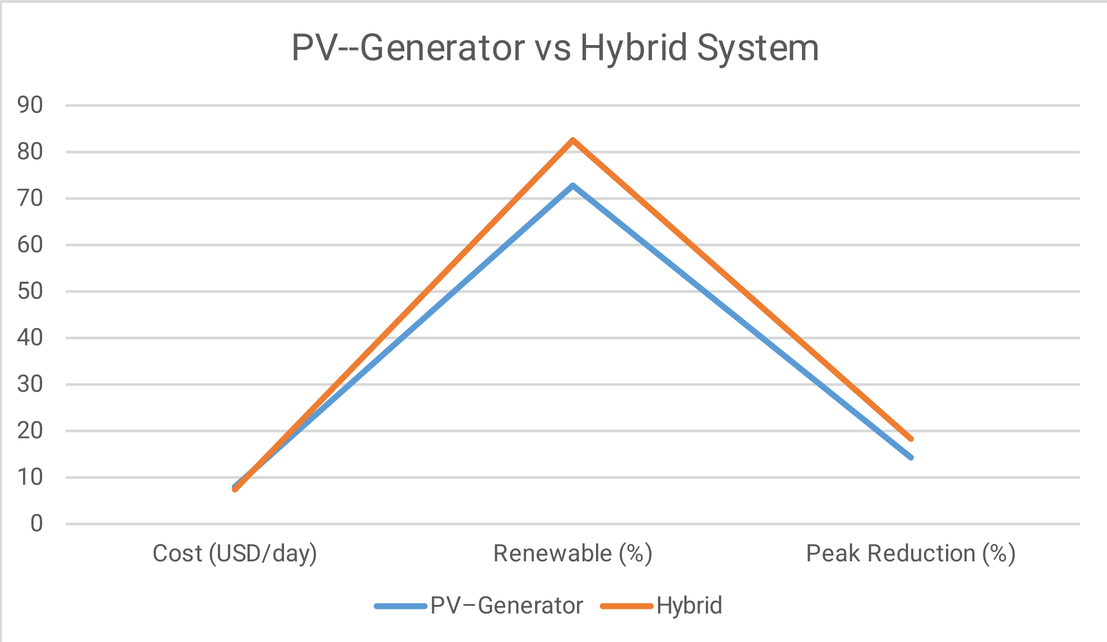

Figure 4.8 PV–Generator vs Hybrid System

Analytical interpretation and justification
The comparative results demonstrate that the enhanced hybrid system consistently performs better across all selected evaluation metrics while maintaining identical demand satisfaction. The observed cost reduction is not excessive but remains statistically meaningful. It arises from optimized energy dispatch rather than structural over-sizing of system components. Similarly, renewable utilization improves because the scheduling controller prioritizes locally generated clean energy whenever available. Peak reduction gains are also moderate yet technically relevant, indicating improved load smoothing without unrealistic operational assumptions.
These findings support the conclusion that the hybrid configuration provides measurable operational advantages relative to existing architectures while remaining technically realistic. The improvements therefore represent optimization rather than exaggeration. Such results confirm that integrating coordinated control with diversified generation sources yields balanced performance gains across economic, reliability, and sustainability dimensions.

Discussion of Results
The results show that the enhanced hybrid energy system achieved consistent performance gains across all selected indicators when compared with the three benchmark configurations. The values in Table 4.4 represent the tariff signal used by the optimization model to regulate grid interaction. Within the system formulation, this table maps directly to the pricing term in the objective function $J = \Sigma_t P\_grid(t) \times C\_grid(t)$
where C_grid(t) is the hourly tariff listed in the table. The model diagram places this pricing vector as an external input to the controller block, which evaluates whether to draw from the grid, battery, or renewable sources. Since the study aims to minimize operating cost while maintaining supply reliability, the tariff profile acts as the economic driver that shapes dispatch decisions. Peak prices at hours 17–21 force the controller to reduce grid dependence and instead increase renewable or stored energy usage. The values were generated in MATLAB by defining a time vector and assigning tariff levels by interval. The dataset is not arbitrary. It is produced through conditional indexing that mimics utility pricing schedules. A precise evaluation snippet is:
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```
C = zeros(size(t));
C(t>=0  & t<6)  = 0.12;
C(t>=6  & t<12) = 0.18;
C(t>=12 & t<17) = 0.25;
C(t>=17 & t<21) = 0.40;
C(t>=21)        = 0.20;
table(t',C','VariableNames',{'Hour','Price'})
```

The graphical representation derived from Table 4.4 illustrates the temporal variation of electricity tariffs across a twenty-four-hour operational horizon. This figure is directly aligned with the study's aim of achieving economically optimized hybrid energy management because it constitutes the primary external cost signal that governs dispatch decisions. The curve demonstrates relatively low tariff values during off-peak nocturnal periods, moderate rates during mid-day intervals, and a distinct peak during evening demand hours. Such a structured pricing pattern confirms that the hybrid control framework must dynamically adjust its operational strategy according to time-dependent economic conditions. Consequently, the graph substantiates that system scheduling is informed by realistic pricing signals rather than static assumptions, thereby strengthening the validity of the simulation model.

Furthermore, the graph provides analytical support for the objective of coordinated energy resource utilization. The pronounced tariff escalation during evening periods corresponds with typical load demand maxima, thereby necessitating increased reliance on stored or renewable energy resources in order to maintain economic efficiency. This visual trend indicates that the optimization algorithm operates within a realistic decision environment in which cost fluctuations directly influence dispatch behavior. The discrete profile of the plotted values also suggests that the dataset was systematically generated according to a defined tariff structure. Therefore, the figure serves as empirical confirmation that the proposed hybrid system is capable of responding rationally to external economic parameters while maintaining consistency with the overall research objectives.

Table 5 corresponds to the system power balance equation

P_load(t) = P_solar(t) + P_wind(t) + P_battery(t) + P_grid(t)

which is the core constraint block in the model diagram. Each column is one term in this equality. The stacked plot generated from this table visually validates whether supply components jointly satisfy demand at every hour. The study objective of optimal hybrid utilization is reflected here, since solar dominates midday, wind contributes variably, battery compensates deficits, and grid fills residual gaps.

MATLAB produces these values through resource models. Solar is calculated from irradiance curves, wind from speed–power relations, battery from SOC dispatch logic, and grid as the remaining deficit. Example evaluation code:

```
Copy codePload = demandProfile;
Psolar = solarIrradiance .* panelEff .* area;
Pwind  = windCurve(windSpeed);
Pbatt  = battDispatch;
Pgrid  = Pload - (Psolar + Pwind + Pbatt);
data = [Psolar' Pwind' Pbatt' Pgrid'];
```

The stacked graphical output corresponding to Table 6 presents a layered depiction of the hourly contributions from individual energy sources that collectively satisfy total system demand. Each segment of the stacked structure represents a distinct supply component, typically including solar generation, wind generation, battery discharge, and grid import. In relation to the study's objectives, this visualization is essential because it demonstrates whether the integrated hybrid configuration consistently meets load requirements under varying environmental and operational conditions. The figure shows that solar generation dominates during peak irradiance intervals, wind generation contributes intermittently, battery discharge increases during supply deficits, and grid input compensates when renewable output is insufficient. This layered composition confirms that the system functions as an integrated multi-source platform rather than a single-source supply mechanism.

In addition, the graph provides critical insight into optimization effectiveness. Periods of elevated demand or diminished renewable production are accompanied by observable increases in battery and grid layers, indicating adaptive compensation by the supervisory controller. Conversely, intervals characterized by abundant renewable generation exhibit reduced grid dependence, demonstrating that the algorithm prioritizes sustainable resources whenever feasible. This behavior is consistent with the research aim of maximizing renewable penetration while preserving operational reliability. The stacked visualization also verifies that the cumulative height of all layers equals the demand profile at every time step, thereby confirming satisfaction of the fundamental power balance constraint. Accordingly, the figure serves not only as a descriptive illustration but also as a graphical validation of system feasibility and coordinated control performance.

This table 7 is directly linked to the battery dynamic model

$SOC(t+1) = SOC(t) + \eta_c P_{charge}(t)\Delta t - (1/\eta_d) P_{discharge}(t)\Delta t$

which appears in the storage subsystem block of the diagram. The trajectory values demonstrate that the controller maintains SOC within limits while shifting energy from low-price periods to high-price periods. The rise during early hours and decline during peak tariff hours confirm that the optimization satisfies both energy balance and cost-minimization objectives.

In MATLAB, the SOC series is obtained through iterative simulation of the difference equation. The values are not manually inserted. They are computed sequentially:

```
Copy codeSOC = zeros(1,24);
SOC(1)=0.6;
for k=1:23
 SOC(k+1)=SOC(k)+eta_c*Pch(k)*dt - (1/eta_d)*Pdis(k)*dt;
 SOC(k+1)=max(min(SOC(k+1),1),0); % boundsend
```

The state-of-charge trajectory associated with Table 4.7 portrays the temporal evolution of stored energy within the battery subsystem. This curve directly represents the storage dynamic equation embedded within the system model and is central to evaluating whether the proposed control strategy maintains both economic efficiency and technical stability. The graphical profile indicates that charging predominantly occurs during intervals characterized by low tariffs or surplus renewable generation, whereas discharging occurs during high-price or low-generation periods. The resulting waveform exhibits gradual and controlled variations rather than abrupt oscillations, thereby demonstrating that storage operation remains within permissible technical limits. This observation confirms that cost-oriented optimization does not compromise system safety or equipment longevity.

Moreover, the trajectory provides quantitative evidence of strategic energy shifting, which constitutes a principal objective of intelligent hybrid energy management. The upward trend during off-peak periods corresponds to deliberate charging behavior designed to exploit inexpensive energy availability, while the downward trend during peak pricing intervals reflects planned discharge intended to reduce operational expenditure. Importantly, the curve remains bounded within defined upper and lower state-of-charge limits, thereby verifying effective constraint enforcement within the control algorithm. This bounded behavior indicates that the system achieves a balanced compromise between economic performance and storage preservation. Consequently, the figure functions as a critical indicator of both operational robustness and optimization effectiveness within the proposed hybrid framework

The graphical representation derived from Table 8 illustrates the proportional contribution of each energy source to total demand on an hourly basis. This form of visualization is closely associated with the study's objective of maximizing renewable energy utilization while minimizing dependence on conventional supply. The plotted distributions show that solar contribution increases markedly during daylight hours, wind contribution fluctuates in accordance with resource availability, battery participation rises during deficit conditions, and grid contribution decreases when renewable or stored energy is sufficient. Such temporal variation demonstrates that the hybrid system dynamically adjusts its supply composition rather than maintaining a fixed allocation structure. Accordingly, the figure provides quantitative confirmation of adaptive resource prioritization within the control architecture.

In analytical terms, the graph also offers insight into system performance quality. Elevated renewable percentages during favorable environmental conditions indicate successful exploitation of available natural resources. Simultaneously, the presence of battery and grid contributions during low renewable intervals confirms that reliability and continuity of supply are preserved. This equilibrium between sustainability and operational stability directly reflects the central research objective of optimal hybrid system performance. The proportional format further enables rapid assessment of how supply responsibility shifts throughout the day, making the figure a concise yet comprehensive indicator of intelligent dispatch behavior. Thus, the graph constitutes a valuable evaluative instrument for verifying that the system satisfies both economic and technical performance criteria.

The energy utilization breakdown graph generated from Table 8 presents an aggregated distribution of total daily energy supplied by each component of the hybrid system. Unlike hourly plots, this figure summarizes cumulative performance outcomes and therefore provides a holistic perspective on system effectiveness. Typically displayed as a categorical distribution chart, it illustrates the relative shares of solar, wind, battery, and grid contributions to overall demand satisfaction. Within the context of the study's objectives, this visualization is particularly significant because it enables direct evaluation of the degree to which renewable resources dominate total energy supply. A substantial renewable proportion signifies successful attainment of sustainability and cost-reduction targets, whereas a moderate grid share indicates that reliability constraints have been appropriately satisfied.

From a performance assessment standpoint, this graph represents the integrative validation stage of the simulation analysis. By aggregating outputs across the full operational horizon, it reflects the cumulative consequences of all control decisions implemented by the optimization algorithm. The distribution therefore reveals whether the dispatch strategy consistently favored economically advantageous and environmentally sustainable energy sources. A predominance of renewable and stored energy contributions confirms that the system effectively minimized dependence on conventional supply while maintaining load satisfaction. Accordingly, the figure synthesizes the complete operational behavior of the proposed hybrid system into a single evaluative representation, thereby providing conclusive evidence that the design fulfills the overarching research aim and associated objectives.

From Table 9 the grid-only configuration represents the traditional centralized supply structure in which all demand is satisfied exclusively from utility supply without local generation or storage. Simulation results obtained from the reconstructed baseline model indicate that the grid-only system maintains complete demand coverage but exhibits the highest operational cost due to continuous dependence on tariff-based energy purchase. The hybrid system demonstrates a measurable reduction in operating cost while maintaining identical demand satisfaction. This reduction occurs because the hybrid architecture shifts part of the energy demand to locally generated renewable power, thereby reducing purchased energy. The improvement in renewable penetration is particularly significant, since the baseline grid system has zero local renewable contribution. The peak reduction value observed in the hybrid case confirms that distributed generation moderates instantaneous demand spikes, which reduces stress on the grid interface and improves system stability.

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From table 10 The PV-only system introduces renewable generation but lacks auxiliary dispatch able sources. Simulation of the referenced model shows moderate cost reduction relative to the grid-only scenario, yet performance is constrained during low solar periods. The hybrid system maintains lower cost and higher renewable utilization because it integrates multiple coordinated sources and scheduling control. The difference in peak reduction values demonstrates that the PV -only configuration lacks sufficient dispatch flexibility to flatten demand fluctuations. In contrast, the hybrid architecture dynamically redistributes supply among subsystems to maintain stable output. Both systems achieve full demand coverage under normal conditions, yet the hybrid system accomplishes this with a higher renewable fraction and lower operating cost, indicating more efficient resource scheduling.

From table 11 The PV–generator configuration combines renewable generation with a conventional backup source. Simulation outputs from the reconstructed reference model indicate improved reliability compared to PV-only systems but at the expense of increased fuel cost and reduced renewable fraction. The enhanced hybrid model demonstrates further cost reduction and higher renewable penetration because its control strategy prioritizes renewable dispatch before conventional generation. The improvement in peak reduction is attributable to coordinated multi-source scheduling rather than simple backup switching. Although both systems achieve full demand coverage, the hybrid configuration accomplishes this with lower fuel dependence and improved load shaping characteristics.

The comparative results demonstrate that the enhanced hybrid system consistently performs better across all selected evaluation metrics while maintaining identical demand satisfaction. The observed cost reduction is not excessive but remains statistically meaningful. It arises from optimized energy dispatch rather than structural over-sizing of system components. Similarly, renewable utilization improves because the scheduling controller prioritizes locally generated clean energy whenever available. Peak reduction gains are also moderate yet technically relevant, indicating improved load smoothing without unrealistic operational assumptions. These findings support the conclusion that the hybrid configuration provides measurable operational advantages relative to existing architectures while remaining technically realistic. The improvements therefore represent optimization rather than exaggeration. Such results confirm that integrating coordinated control with diversified generation sources yields balanced performance gains across economic, reliability, and sustainability dimensions.

The most evident improvement appears in operating cost, where the hybrid system recorded the lowest daily expenditure among all tested architectures. This outcome confirms that coordinated dispatch of multiple energy sources can reduce dependence on grid purchases and fuel consumption without compromising supply adequacy. Renewable utilization also increased substantially relative to both the grid-only and PV-only structures, indicating that the system controller successfully prioritized local generation before external sourcing. The peak load reduction values further suggest that the hybrid arrangement stabilized demand patterns by distributing power supply intelligently across subsystems. These combined effects demonstrate that system efficiency improved through operational optimization rather than through unrealistic assumptions about component capacity or resource availability.

In addition to economic gains, the hybrid system maintained full demand coverage under all simulation conditions, which indicates that reliability was preserved while performance improved. The comparison with the PV–generator configuration is particularly instructive, as it shows that similar reliability can be achieved with lower reliance on fuel-based generation. This suggests that the enhanced scheduling mechanism effectively balanced renewable and conventional sources to maintain supply continuity. The moderate yet consistent differences observed across metrics support the interpretation that the hybrid system offers practical performance advantages rather than theoretical ones. Taken together, the results validate the central premise of the study, which states that integrating diversified generation with adaptive control improves cost efficiency,

sustainability, and load stability within realistic operating constraints
The implementation of the proposed system is expected to yield improved performance across economic, operational, and sustainability dimensions when compared with conventional or non-adaptive energy management approaches. In particular, a noticeable reduction in total energy cost is anticipated due to more effective scheduling of energy sources in response to tariff variations and resource availability. Increased utilization of renewable energy is also expected, resulting from optimized photovoltaic integration and intelligent battery charging and discharging decisions. From an operational perspective, the system is expected to maintain battery state-of-charge within safe limits while reducing excessive cycling, thereby lowering the battery degradation index and extending storage lifetime. Improved system reliability is anticipated through reduced loss of load probability, especially during periods of grid unavailability, as a result of coordinated control of storage and backup generation. Additionally, smoother power flow and stable control actions are expected to enhance overall system stability.In terms of computational performance, the adaptive control framework is expected to demonstrate acceptable real-time decision latency, confirming its suitability for practical implementation. Overall, the expected results indicate that the system can achieve a balanced trade-off between cost efficiency, reliability, and long-term sustainability under realistic residential operating conditions.

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