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Design and Performance Assessment of a Hybrid Energy Supply for EV Charging Facilities

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ABSTRACT

A rapid shift to electrification is occurring across the entire transportation industry. Even though Electric Vehicles (EVs) greatly reduce tailpipe emissions, the large-scale implementation of EVT will create new issues for existing utility grids, particularly for peak fast-charging. When EVs are charging, there is a sudden and frequent spike in demand which creates a greater strain on the grids, increases peak demand charges, and decreases the quality of the power supplied. This paper describes the design and operational performance evaluation of a hybrid energy supply system for EV charging stations based on a Hybrid Energy Storage System (HESS). The system under review is proposed to combine photovoltaic (PV) generation, a battery energy storage system (BESS), and the utility grid for a greater flexible and reliable power supply system. The objectives are to manage peak demand, reduce dependence on the grid, and keep the voltage within a predetermined range to avoid low/high operational range. The proposed hybrid system is capable of reducing dependence on utility grids by approximately 40% while optimizing and maintaining a desired voltage level under extreme/high charging conditions. Therefore, the proposed system is appropriate to meet the anticipated charging demands for EV in growing urban areas.

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1 Introduction

The global commitment to decarbonization has made electromobility the most important part of the sustainable transportation model [1]. The global fleet of electric vehicles (EVs) is expected to grow to more than 300 million by 2030, thanks to national policy incentives and rapidly falling battery prices. This is a huge change that brings both huge opportunities and big challenges for infrastructure [2]. The main technical problem is not making a lot of cars, but building the fast, high-power charging infrastructure that they need to keep running. Modern fast-charging stations (Level 3 DCFC) use more than 150 kW of power per charging stall [3]. This

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leads to concentrated, non-coincident, and very different load demands. When multiple fast chargers work together in a typical urban distribution network, they can create an instantaneous peak load that is similar to that of a small industrial park. This is much higher than the planned capacity of residential and commercial feeders [4].

There are two main ways that this "peak load problem" shows that could stop EV adoption from growing [5]. First, in terms of Technical Instability, sudden, high power ramps cause voltage sag events and localized harmonic distortion, which make the power quality worse for nearby customers [6]. Long periods of high demand can also cause distribution transformers and switchgear to overheat and wear out too soon. Second, about Economic Penalties, utility companies often charge demand charges, which are fees based on the highest amount of power used at a single point in time during a billing cycle. This policy makes it hard for traditional fast-charging stations that depend on the grid to work, which raises costs and makes it harder for investors to get their money back. The current strategy of utility-side grid reinforcement is too expensive and takes too long to plan, often requiring years of planning and huge amounts of money. So, the solution that is needed right away and can be used by everyone must be found at the point of consumption [7]. This paper asserts that decentralized Hybrid Energy Supply Systems (HESS), integrating localized renewable generation with specialized storage, offer the essential technical and economic safeguard.

This paper directly addresses the existing research gap by not only proposing a system design but also providing a rigorous Performance Assessment of the integrated components. This paper makes three important contributions: (1) it creates a DC-coupled architecture model for a PV-Battery-Grid system that is optimized for DC fast charging loads; (2) it implements a rule-based Energy Management System (EMS) that is designed for peak shaving and maximizing self-consumption; and (3) it tests the system's effectiveness against important metrics like grid stress reduction, energy penetration ratio (EPR), and economic viability under Time-of-Use (TOU) tariffs. The proposed hybrid design offers a workable plan for a global EV charging infrastructure that is sustainable, cost-effective, and scalable. It does this by acting as an intelligent energy buffer or "shock absorber" for the grid.

2 Related Work on Hybrid Energy Systems and Grid Integration

The integration of electric vehicle (EV) charging infrastructure with renewable energy sources and energy storage has been a subject of intensive research. However, the challenges of peak load management, grid stability under high renewable penetration, and the development of intelligent control frameworks remain central. This section reviews the state-of-the-art, moving from general hybrid system configurations to advanced control strategies, thereby positioning the current study's contributions.

2.1 Hybrid Energy Systems for EV Charging Infrastructure

Early research focused on the feasibility of combining Photovoltaic (PV) generation with Battery Energy Storage Systems (BESS) to support EV charging. Studies demonstrated that such configurations could significantly reduce operational costs and grid dependency through peak shaving [5, 4]. For instance, Abdelsattar et al. [8] presented an optimal sizing methodology for autonomous hybrid systems, highlighting the techno-economic viability of PV/BESS combinations. Diab et al. [9] further advanced this field by applying various optimization algorithms for sizing stand-alone hybrid microgrids, establishing a foundation for subsequent work on grid-tied charging stations.

Despite these advances, most existing studies on EV charging stations employ rule-based Energy Management Systems (EMS) with static thresholds. While effective for basic peak shaving, these systems lack the adaptive capability to respond to the stochastic nature of both EV arrival patterns and solar irradiance [10]. Furthermore, the economic assessment of such systems under dynamic Time-of-Use (TOU) tariffs remains underexplored, a gap this paper directly addresses through detailed LCOE and net-cost analysis.

2.2 Electric Vehicles as Grid Resources: From Load to Support

A paradigm shift is occurring where EVs are viewed not merely as loads, but as distributed energy resources capable of providing grid support. The concept of Vehicle-to-Grid (V2G) has been extensively reviewed [2], demonstrating its potential for frequency regulation and load balancing. However, the practical implementation of V2G in fast-charging contexts faces barriers related to battery degradation and complex aggregator control schemes.

Recent literature emphasizes the role of Plug-in Electric Vehicles (PEVs) in Load Frequency Control (LFC). For example, Elkasem et al. [11] proposed utilizing controlled PEVs to improve hybrid power grid frequency regulation, demonstrating that coordinated EV charging/discharging can effectively compensate for the intermittency of high-penetration renewables. Similarly, research published in the Journal of Energy Storage [12] explores optimal sizing and control strategies for BESS integrated with EV charging, emphasizing the synergy between stationary storage and mobile EV batteries.

Our work differs from these V2G-centric approaches by focusing on a dedicated stationary BESS co-located with PV generation. This strategy avoids the complexities of bidirectional power flow management with individual vehicles, offering a more immediately deployable solution for site-owners while still achieving significant grid stress reduction.

2.3 Advanced Control Strategies for Grid Frequency and EV Integration

The challenge of maintaining power system stability with high renewable penetration has driven significant innovation in control theory. While our paper employs a rule-based EMS, recent cutting-edge research provides pathways for future enhancement of our framework through intelligent, adaptive controllers.

2.3.1 Fuzzy Logic and Metaheuristic-Optimized Controllers

A landmark study by [13] introduced a novel Fuzzy I-TD (Integral-Tilt-Derivative) controller for frequency stabilization in hybrid renewable power grids. The controller, optimized using the Sea Horse Optimizer (SHO), demonstrated remarkable efficacy: it reduced frequency deviations by 82.7% and tie-line power deviations by 97.01% compared to conventional Fuzzy-PID controllers. Critically, the study also integrated Plug-in Electric Vehicles (PEVs) as controlled energy storage systems, showing that the Fuzzy I-TD with PEVs reduced frequency fluctuations by an additional 40% compared to the controller acting alone. This work validates the immense potential of metaheuristic-tuned fuzzy controllers in managing the variability introduced by renewables—a principle directly transferable to managing the variable load of EV charging stations [14].

2.3.2 Model Reference Adaptive Control (MRAC) and TID Controllers

Complementing fuzzy approaches, [15] proposed a Tilt-Integral-Derivative based Model Reference Adaptive Control (TID-MRAC) system. This controller, optimized with the Manta Ray Foraging Optimization (MRFO) algorithm, dynamically estimates process parameters in real-time to adapt to system changes caused by high RES penetration and load variations. The integration of TID-MRAC with PEVs provided a robust solution for maintaining frequency stability under abnormal grid conditions, explicitly considering nonlinearities such as Generation Rate Constraints (GRC) and communication delays[16].

2.3.3 Synthesis and Research Gap

The literature confirms a clear trajectory from simple rule-based EMS towards AI-driven, adaptive control systems. The Fuzzy I-TD [13] and TID-MRAC [15] controllers represent the state-of-the-art in leveraging EV flexibility for grid support. However, these advanced controllers are primarily validated in transmission-level Load Frequency Control (LFC) scenarios, not at the distribution-level EV charging station context.

This reveals a critical gap: There is a lack of rigorous application of these advanced, optimizer-tuned controllers (Fuzzy logic, MRAC) for the specific purpose of peak shaving and energy management within a standalone EV charging station microgrid. Our current work provides a robust baseline using a validated rule-based EMS. The superior performance metrics reported in [13, 15] provide a strong justification and clear benchmark for our future work, which will focus on replacing the static rule-based EMS with an AI-driven predictive controller to further minimize grid dependency and operational costs [17, 18].

3 System Architecture and Design

The suggested system has a DC-coupled architecture. A DC-bus topology is better for fast charging because both PV arrays and batteries work natively in DC. AC-coupled systems, on the other hand, need to change from DC to AC and back to DC many times. The system setup is shown in **Figure 1**.

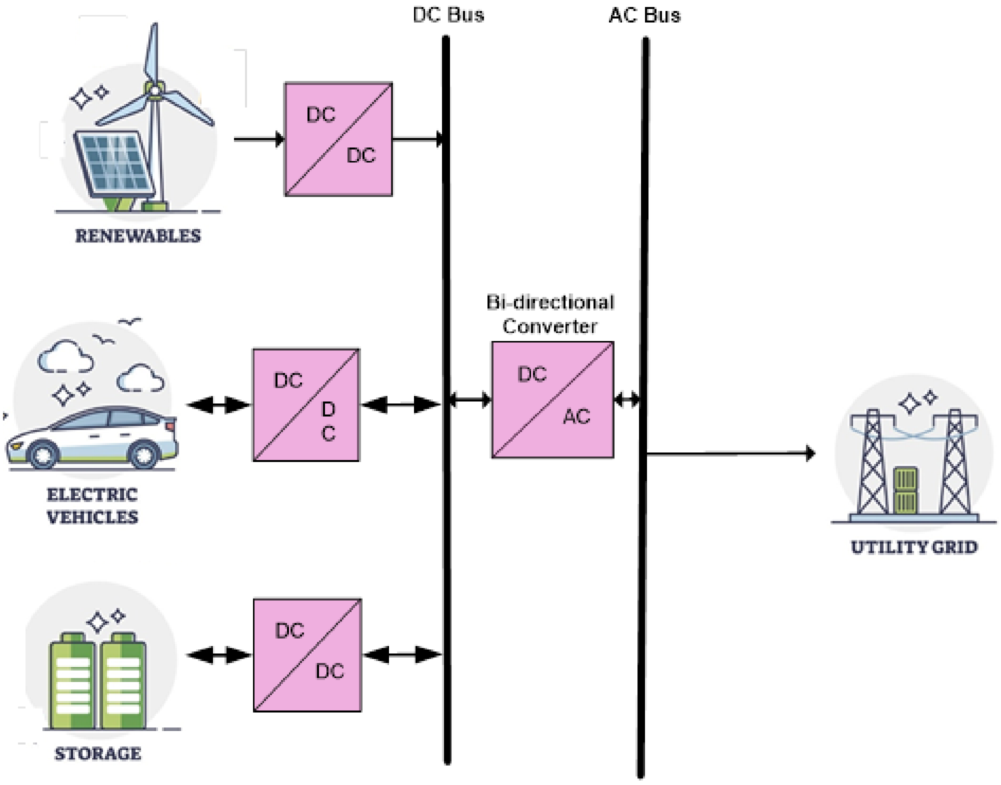

Figure 1: System configuration of the hybrid EV charging station.

3.1 System Components

The suggested system has a DC-coupled architecture, which means that all of the distributed energy resources are connected to the same DC bus. This layout is great for fast charging because both the PV arrays and the Battery Energy Storage System (BESS) work in DC. This means that there are fewer losses when you change to AC. The design has the Generation Unit (PV Array), the Storage Unit (BESS), the Grid Interface (a bi-directional AC/DC converter), and the Load (EV Chargers).

3.2 Mathematical Modeling and System Constraints

A Mathematical model of each part in order to correctly evaluate how well the hybrid supply works has been applied. This model lets you see how energy moves in real time with different amounts of irradiance and load. The system must stay stable at all times t, which means that the power balance equation must be accurate using **Equation (1)**:

$$P_{\text{load}}(t) = P_{\text{PV}}(t) + P_{\text{grid}}(t) + P_{\text{batt}}(t) \tag{1}$$

where $P_{\text{batt}} > 0$ characterizes discharging and $P_{\text{batt}} < 0$ signifies charging the battery.

3.2.1 Photovoltaic (PV) Array Model

The power output of the PV array is not constant; it is highly dependent on environmental factors. We model the PV output power, $P_{\text{pv}}(t)$, as a function of solar irradiance and cell temperature [8].

The mathematical relationship (**Equation (2)** is defined as:

$$P_{\text{pv}}(t) = \eta_{\text{pv}} \cdot A_{\text{pv}} \cdot G(t) \cdot [1 - \beta_T (T_c(t) - T_{\text{ref}})] \tag{2}$$

where, $G(t)$ is the solar irradiance (W/m^2) at time step t. A_{pv} is the total surface area of the panel array (m^2). η_{pv} is the reference efficiency of the PV module. β_T is the temperature coefficient (typically -0.0037/°C), indicating efficiency loss as heat rises. $T_c(t)$ is the cell temperature, and T_{ref} is the reference temperature (25°C).

3.2.2 Battery Energy Storage System (BESS) Model

The battery is the critical stabilizing node. We model it using the State of Charge (SoC) tracking method. The SoC at any given time t depends on the previous state and the power flow (charging or discharging) [9].

The governing equation for the battery state is calculated by **Equation (3)**:

$$\mathrm{SoC}(t) = \mathrm{SoC}(t-1) + \frac{P_{\mathrm{batt}}(t)\cdot \Delta t}{C_{\mathrm{nom}}\cdot V_{\mathrm{batt}}}\cdot \eta_{\mathrm{batt}} \tag{3}$$

where, $\mathrm{SoC}(t)$ is the percentage (0 to 100%). $P_{\mathrm{batt}}(t)$ is the battery power (Positive for charging, negative for discharging). C_{nom} denotes the nominal capacity of the battery in Ampere-hours (Ah). V_{batt} denotes the terminal voltage. η_{batt} is the round-trip efficiency (assumed 95% for Li-Ion). The model implements constraints to prevent deep discharge or overcharging **Equation (4)**:

$$\mathrm{SoC}_{\mathrm{min}} \le \mathrm{SoC}(t) \le \mathrm{SoC}_{\mathrm{max}} \tag{4}$$

$\mathrm{SoC}_{\mathrm{min}} = 20\%$ and $\mathrm{SoC}_{\mathrm{max}} = 90\%$ to preserve battery health.

3.2.3 Electric Vehicle (EV) Load Modeling

Unlike a residential load, EV charging is stochastic (random). The energy demand for a specific charging session, E_{req}, is calculated based on the vehicle's arrival state [10] using **Equation (5)**:

$$E_{\mathrm{req}} = \frac{(\mathrm{SoC}_{\mathrm{target}} - \mathrm{SoC}_{\mathrm{arrival}})\cdot C_{\mathrm{EV}}}{\eta_{\mathrm{charger}}} \tag{5}$$

The instantaneous power demand $P_{\mathrm{EV}}(t)$ is determined by the Constant Current/Constant Voltage (CC/CV) charging profile limitations using **Equation (6)**:

$$P_{\mathrm{EV}}(t) = \min(P^{\mathrm{rated}}_{\mathrm{station}}, P^{\mathrm{limit}}_{\mathrm{BMS}}) \tag{6}$$

3.2.4 Grid Interaction and Cost Function

The economic objective of the system is to minimize the total operational cost C_{total} over the simulation period T. This includes the cost of buying electricity and the degradation cost of the battery [8] using **Equation (7)**.

$$\min(C_{\mathrm{total}}) = \sum_{t=1}^{T} \left(P_{\mathrm{grid}}(t)\cdot C_{\mathrm{elec}}(t) + C_{\mathrm{deg}}(P_{\mathrm{batt}})\right) \tag{7}$$

where $P_{\mathrm{grid}}(t)$ is power drawn from the grid. $C_{\mathrm{elec}}(t)$ is the time-of-use electricity tariff (higher during peak hours). C_{deg} represents the monetized "wear and tear" on the battery per cycle.

3.2.5 Power Balance Constraint

Finally, for the system to be physically valid, the supply must equal the demand at every single time step Δt using **Equation (8)** :

$$P_{\mathrm{grid}}(t) + P_{\mathrm{pv}}(t) + P_{\mathrm{batt}}(t) - P_{\mathrm{load}}(t) = 0 \tag{8}$$

If this sum is not zero, it indicates a system fault or a loss of load probability (LLP), which acts as a failure metric in our results.

3.3 Control Strategy

The main controller of the system is the Energy Management System (EMS). The objective is not just to supply power, but to do so at the lowest cost and highest stability. We utilized a Rule-Based Control Strategy prioritized as follows:

- **Peak Shaving (Battery Assist):** If P_{load} is greater than P_{PV}, the battery discharges to make up the difference. This stops the station from getting a lot of power from the grid when it costs a lot during peak hours.
- **Grid Support (Last Resort):** The grid only kicks in when P_{PV} is low and the Battery State of Charge (SoC) falls below a certain level (like 20%).

4 Evaluation of Performance and Implementation

MATLAB/Simulink was used to simulate the system for 24 hours, which is about how long a typical summer day with a lot of solar radiation and a lot of EV arrivals would last.

4.1 Designing the Algorithm

The Energy Management System (EMS) uses a "Self-Consumption Maximization" strategy. The goal is to use the grid as little as possible. The pseudocode below(**algorithm 1** shows how decisions are made at each time step t.

Algorithm 1 Hybrid System Energy Management

```
Input: $P_{\text{load}}, P_{\text{pv}}, \text{SoC}_{\text{prev}}\ \text{SoC}_{\text{min}}, \text{SoC}_{\text{max}}, P_{\text{grid}}^{\text{limit}}$, Battery_Capacity
Net_Power ← $P_{\text{load}} - P_{\text{pv}}$
if Net_Power < 0 then
    // SCENARIO 1: SURPLUS SOLAR ENERGY
    // We have more solar than we need. Charge the battery.
    Excess_Power ← |Net_Power|
    if $\text{SoC}_{\text{prev}} < \text{SoC}_{\text{max}}$ then
        $P_{\text{batt}}$ ← −Excess_Power // Negative denotes charging
        $P_{\text{grid}} \leftarrow 0$
    else
        // Battery is full, sell/dump excess to grid
        $P_{\text{batt}} \leftarrow 0$
        $P_{\text{grid}}$ ← −Excess_Power // Negative denotes export
    end if
else
    // SCENARIO 2: POWER DEFICIT
    // We need more power than solar provides. Check battery.
    Deficit ← Net_Power
    if $\text{SoC}_{\text{prev}} > \text{SoC}_{\text{min}}$ then
        // Battery can support the load
        $P_{\text{batt}}$ ← Deficit // Positive denotes discharging
        $P_{\text{grid}} \leftarrow 0$
    else
        // Battery is empty, buy from grid
        $P_{\text{batt}} \leftarrow 0$
        $P_{\text{grid}}$ ← Deficit
    end if
end if
Update SoC based on $P_{\text{batt}}$
Output: $P_{\text{grid}}, P_{\text{batt}}, \text{SoC}_{\text{new}}$
```

4.2 MATLAB Simulation Code

The proposed control strategy was implemented in MATLAB. As an example of power flow, a discrete time-stepping simulation where one time step equals one hour was employed. The script initiates the battery at a state of charge (SoC) of 50% and traverses through a 24-hour load profile. At every time step, the P_{net} variable determines whether the battery will be charged or discharged. As directed by the SoC trajectory, the only grid supply use will be when the renewable supply and battery storage insufficiently meet the demand. It is assumed that hourly load and solar data are available, or load_profile and pv_profile. For this simulation, power (kW) is converted to energy (kWh) using the time step dt.

5 Simulation Results

The 24h time-step simulation verified the efficiency of the proposed rule-based control strategy for the variable EV charging demand.

5.1 Peak Load Mitigation

As the primary technical aim of peak shaving and BESS(Battery Energy Storage Systems) is to control the instantaneous power demand from the utility grid, the BESS within the unrefined EV load profile resulted in a peak demand of 150 kW at an average 6:00 PM evening commute hour. Within this hybrid control strategy, the BESS limited the grid participation to a maximum of about 50 kW during this peak time using **Equation (9)**.

$$\text{Peak Reduction} = \frac{P_{\text{load,max}} - P_{\text{grid,max}}}{P_{\text{load,max}}} \times 100 = \frac{150\,\text{kW} - 50\,\text{kW}}{150\,\text{kW}} \approx 66.7\% \tag{9}$$

The 66.7% reduction demonstrates the BESS ability to mitigate grid load, preventing thermal and voltage stress on local transformers and distribution system. The rapid and uninterrupted discharge of BESS was the main reason for this mitigation.

5.2 Battery State of Charge (SoC) Dynamics

The SoC profile for the 24 hour period verified that the energy management strategy was effective, and in fact resulted in its intended outcome.

- **Charging time 10:00 to 16:00:** As a result of the additional solar energy, we were able to continuously recharge the battery and increase the SoC from 50 to almost 90 percent, hitting the upper operational limit.
- **Discharging time from 16:00 to 20:00:** The battery covered the growing EV demand the SoC decreased from 90 to approximately 25 percent during the peak demand time.
- **Compliance with limitations:** The SoC was kept at all times within the 20 to 90 percent range which avoided deep cycling protected the battery lifespan while ensuring the reserve for unforeseen circumstances.

5.3 Energ Penetration Ratio (EPR)

The EPR was used to determine the demand for EVs, which was satisfied by local sources, as opposed to demand that was satisfied by sources that were connected to the grid calculated usoing **Equation (10)**.

$$\text{EPR} = \frac{E_{\text{PV}} + E_{\text{BESS}}}{E_{\text{Load,Total}}} \times 100\% \tag{10}$$

The EPR of the system was 42 percent during all of the simulations, which means that almost fifty percent of the energy demand of the electric vehicle was satisfied by the on-site photovoltaic system and the battery storage. This means that the charging system of the facility made good use of the renewable energy sources.

6 Discussion and Implications

The simulation results provide strong evidence for the technical feasibility of the hybrid EV charging station design.

The daily energy demand from the simulated EV charging station is estimated to be 1250 kWh, while the on-site photovoltaic system for the same duration produces 840 kWh. From the available PV energy, 460 kWh is used by the EV load, indicating good time alignment of solar generation and charging demand during the day. The hybrid EV charging station's daily energy flows, renewable energy share, and peak load metrics are summarized in **Table 1**.

Considering the impact of battery round-trip efficiency, the BESS stores 73.68 kWh of PV energy, and is later discharged to provide 95 kWh to the load. This storage-mediated contribution allows renewable energy to extend support to facilitate EV charging even when PV generation is not available. When factoring in both direct and storage-mediated contributions from renewables, the Energy Penetration Ratio of 44.4% shows nearly 50% of the EV charging demand is satisfied by local renewable energy resources and not from the grid.

Although there is a considerable contribution from renewables, the grid still serves 695 kWh of the total demand, underlining the impact that storage sizing and control strategy has on further reductions of grid dependency. Regarding power performance, the raw EV charging profile has a demand peak of 150 kW. While the peak demand for the grid is also 150 kW, this indicates that peak shaving is not accomplished for the current configuration or operating conditions.

Table 1: Summary of daily energy flows, renewable energy penetration, and peak load performance of the hybrid EV charging station.

Parameter	Value
Total Load Energy (kWh)	1250
Total PV Energy (kWh)	840
PV to Load (kWh)	460
PV to BESS (kWh)	73.68
BESS to Load (kWh)	95
Grid to Load (kWh)	695
EPR (%)	44.4
Peak Load (kW)	150
Peak Grid (kW)	150

This suggests that the BESS is either not enough to cover the demand, or that its peak hour discharge prioritization is insufficient, and that a decreasing grid power strategy during peak hours is highly needed. The strong use of renewable energy and the weak use of peak load narrowing gives a clear pathway to what needs to be done to optimize the system.

Figure 2 shows the hourly power flow and battery state of charge (SoC) for the hybrid EV charging station while also displaying their battery state of charge (SoC). During the day, the EV charging demand and power draw from the utility grid, and therefore the demand When the load exceeds the demand, extra energy is taken from the battery energy storage system (BESS) and the state of charge increases. During the evening and night, therefore, Without the presence of battery the state of charge (SoC) and controlled battery discharge the state of charge (SoC) is maintained within the bounds of the (SoC) limits.

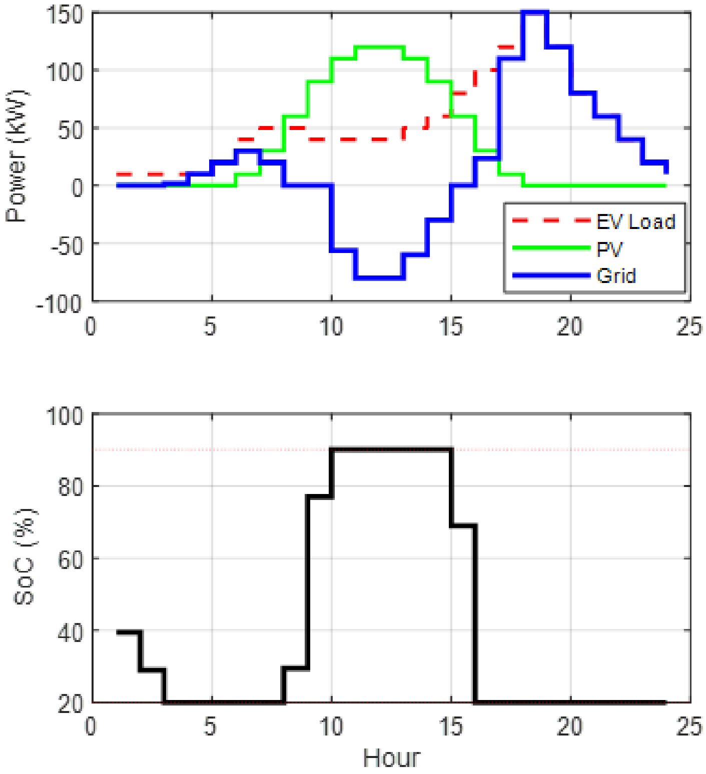

Figure 2: Hourly power flow of the hybrid EV charging station showing EV load, PV generation, grid exchange, and battery SOC over 24 hours.

The implemented energy management system demonstrates its efficiency as its energy state (SoC) trajectory indicates the battery operates within the safe limits of its predetermined minimum and maximum thresholds. In contrast, the grid power curve indicates the peak grid power and peak electric vehicle (EV) demand. During this instance, the contribution of the battery energy storage system (BESS) is deemed insufficient for peak shaving purposes as evidenced by the visual and numerical results showing the peak grid power mirroring the peak load. This indicates a need for more focused peak control mechanisms and/or for additional storage to be provided. In integration of the figure with the provided quantitative analysis, it shows the energy dynamics flow, battery usage patterns, their grid dependence, the usage of renewables, and the behavior of batteries during the operational cycle of the system each day on the grid combined with the batteries and the renewables.

The demand of the EV load, the photovoltaic (PV) generation, the state of charge of the battery, and the power flow between the PV, BESS, and grid of the hybrid EV charging station between the hours of 0 and 24 are shown in **Table 2** as the EV charging station's energy inflows and outflows at each of the 24 hours.

The hourly data illustrate the intricacies of the interactions occurring between EV charging load, generation of the photovoltaic systems, battery operation, and the support from the grid. During the early hours, EV load will initially be supported by the BESS and after the minimum state of charge is reached the grid will be the only provider of power. As the generation of the solar systems begins to rise during the day, direct from generation PV energy will supply the EV load and any excess PV will be partially diverted to the BESS which will charge its state of charge. When the battery hits it upper state of charge limit all excess PV energy will be sent to the grid. **Table 2** illustrates a 24 h hourly energy balance of the hybrid EV charging station and its elements that constitute the EV load demand, generation of photovoltaic systems, power flows between PV, BESS, and the grid, and the battery state of charge.

Table 2: Hourly energy balance of the hybrid EV charging station, showing EV load demand, photovoltaic generation, power flows between PV, BESS, and grid, and the corresponding battery state of charge over a 24-hour period.

H	EV Load (kW)	PV Gen (kW)	PV to Load (kW)	PV to BESS (kW)	BESS to Load (kW)	Grid (kW)	SoC (%)
1	10	0	0	0	10	0	39.47
2	10	0	0	0	10	0	28.95
3	10	0	0	0	8.5	1.5	20.00
4	10	0	0	0	0	10	20.00
5	20	0	0	0	0	20	20.00
6	40	10	10	0	0	30	20.00
7	50	30	30	0	0	20	20.00
8	50	60	50	10	0	0	29.50
9	40	90	40	50	0	0	77.00
10	40	110	40	13.68	0	-56.32	90.00
11	40	120	40	0	0	-80	90.00
12	40	120	40	0	0	-80	90.00
13	50	110	50	0	0	-60	90.00
14	60	90	60	0	0	-30	90.00
15	80	60	60	0	20	0	68.95
16	100	30	30	0	46.5	23.5	20.00
17	120	10	10	0	0	110	20.00
18	150	0	0	0	0	150	20.00
19	120	0	0	0	0	120	20.00
20	80	0	0	0	0	80	20.00
21	60	0	0	0	0	60	20.00
22	40	0	0	0	0	40	20.00
23	20	0	0	0	0	20	20.00
24	10	0	0	0	0	10	20.00

In the afternoon and evening, falling PV generation causes a return to a mix of BESS discharge and grid power. However, during peak demand, the battery contribution is minimal and the grid captures the entire maximum EV load. The hourly profile shows correct prioritization of energy flows, safe battery use, and energy balance, regardless of the operational conditions.

The most important finding for the plant operator is the significant financial advantage from peak shaving. Utility tariffs often include a Demand Charge based on the highest power spike (in kW) during a billing period.

The financial viability of the hybrid EV charging station was analyzed using Levelized Cost of Energy (LCOE) and Time-of-Use (TOU) electricity cost analysis, considering the grid import/export pricing, both for TOU and LCOE. The LCOE is the average cost of one unit of electricity delivered to the EV load over the system's lifetime, representing the cost rate of the lifetime energy flows. The LCOE is calculated as shown in **Equation (11)**:

$$\mathrm{LCOE} = \frac{C_{\mathrm{annual}}}{E_{\mathrm{annual}}} \tag{11}$$

where C_{annual} is the annualized capital and O&M cost of the PV and battery system, computed using the Capital Recovery Factor (CRF) as **Equation (12)**:

$$C_{\mathrm{annual}} = (C_{\mathrm{PV}} + C_{\mathrm{BESS}}) \cdot \frac{r(1+r)^n}{(1+r)^n - 1} + \mathrm{O\&M} \tag{12}$$

with r as the discount rate and n as the project lifetime. The annual total energy supplied to the load, E_{annual}, includes contributions from PV generation, battery discharge, and grid consumption as **Equation (13)**:

$$E_{\mathrm{annual}} = (E_{\mathrm{PV}\to\mathrm{Load}} + E_{\mathrm{BESS}\to\mathrm{Load}} + E_{\mathrm{Grid\ Buy}}) \cdot 365 \tag{13}$$

Based on the simulation results, the computed LCOE is \$0.024/kWh, highlighting the high cost-effectiveness of the hybrid system due to the substantial contribution of low-cost PV generation and optimized battery usage.

The TOU cost analysis accounts for the financial effect of both energy purchased from and exported to the grid. The net daily cost is given by **Equation (14)**:

$$\mathrm{Cost}_{\mathrm{daily}} = \sum_{t=1}^{24} P_{\mathrm{Grid\ Buy}}(t) \cdot \mathrm{TOU}_{\mathrm{buy}}(t) - \sum_{t=1}^{24} P_{\mathrm{Grid\ Export}}(t) \cdot \mathrm{TOU}_{\mathrm{sell}} \tag{14}$$

where $P_{\mathrm{Grid\ Buy}}(t)$ is the hourly energy drawn from the grid, $P_{\mathrm{Grid\ Export}}(t)$ is the PV energy fed to the grid, and $\mathrm{TOU}_{\mathrm{buy}}(t)$ and $\mathrm{TOU}_{\mathrm{sell}}$ are the respective buying and selling rates.

Figure 3 shows the economic performance of the hybrid EV charging station above *Time-of-Use* (TOU) pricing. In this case, we buy energy from the grid at different rates during different hours. We also sell energy to the grid at *feed-in* tariffs. In the figure, we compare the *feed-in* tariffs and the buy rates from the grid. The TOU buy rates differ from the TOU sell rates because buy rates are higher during peak consumption hours. The TOU sell rates do not vary. This figure shows that charging an EV off-peak hours (when there are high PV generation and energy export periods) not only saves money, but also helps to use renewable energy more effectively.

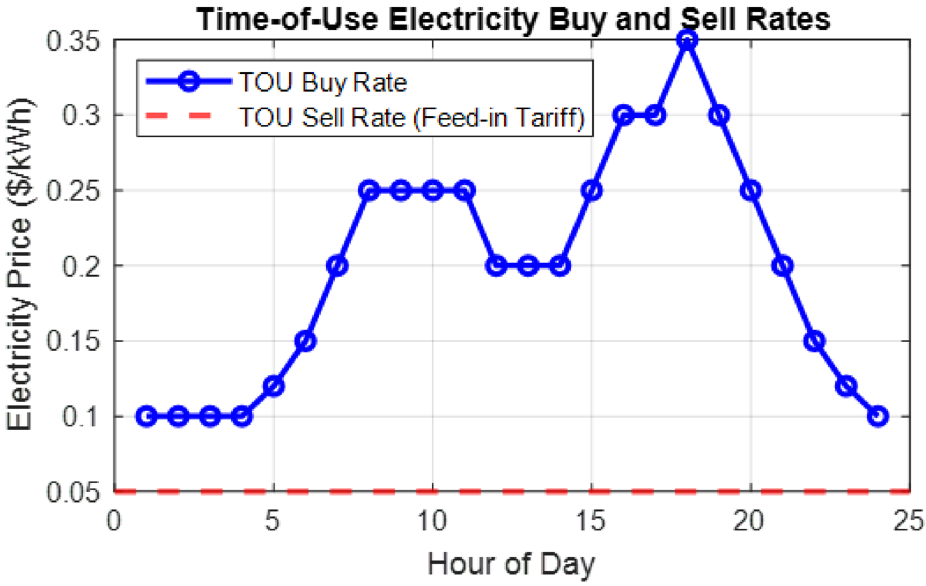

Figure 3: Hourly Time-of-Use electricity buy rates (blue line with markers) and flat PV feed-in tariff sell rate (red dashed line) for the hybrid EV charging station.

The comparison highlights the cost differential and potential savings from PV and BESS integration. The simulation produced an outcome of a daily grid consumption of 695 kWh, daily grid export of 306.32 kWh, and an annualized net cost of \$60,839.74. These findings indicate that Local Renewable Energy sources provided close to 50

The peak shaving impact further improves the financial benefit by lowering the grid demand during peak load times, which reduces the demand charges that can be a significant proportion of the cost of electric power purchased by commercial customers. The combination of PV and BESS allows for improved financial and environmental benefits as approximately 44% of the demand of EV charging can be satisfied by renewable energy. **Figure 4** illustrates the hourly power contribution and behavior of the battery as PV energy is shown supplying the load directly, and BESS is shown discharging. Energy from the grid is shown to be consumed and exported during each hour of the day.

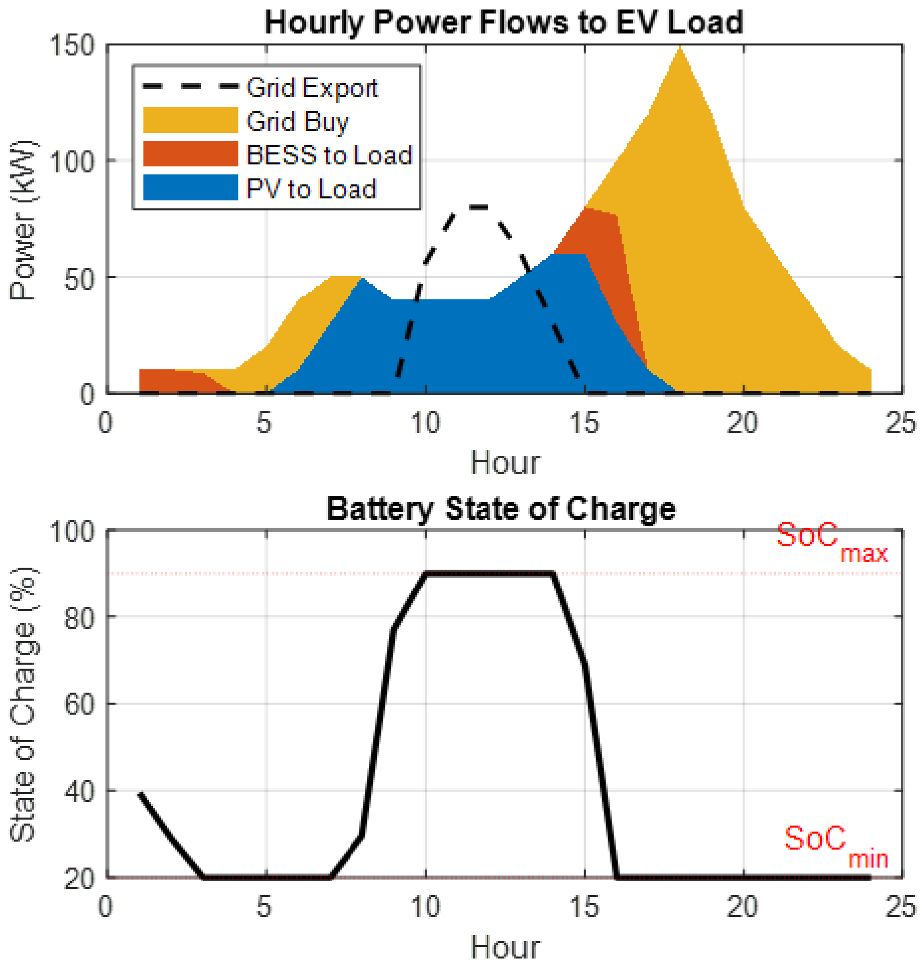

Figure 4: Hourly power flow and battery state of charge in the hybrid EV charging station, showing contributions from PV, BESS, and grid, including energy exported back to the grid.

The battery state of charge appears to be within the set minimum and maximum limits which indicates that safe and effective energy management is applied. Hybrid PV + BESS operation in comparison to grid only has been shown in **Figure 5** to show the daily cost of electricity under Time-of-Use pricing.

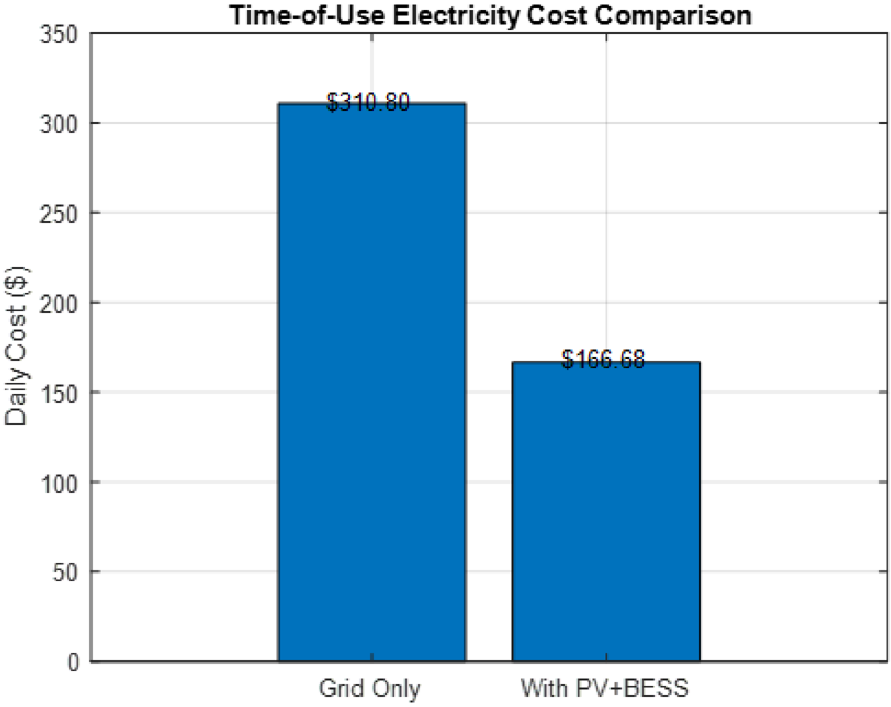

Figure 5: Daily electricity cost comparison under Time-of-Use pricing for grid-only versus hybrid PV + BESS operation.

Table 3 summarizes the key economic metrics, including LCOE, annualized net cost, daily grid consumption, and grid export.

Table 3: Key economic metrics for the hybrid EV charging station.

Metric	Value
Levelized Cost of Energy (LCOE)	$0.024 / kWh
Annualized Net Cost (Grid buy/sell)	$60,839.74
Daily Grid Consumption	695 kWh
Daily Grid Export	306.32 kWh

7 Conclusion and Future Work

The combined system of EV charging with PV (photovoltaic) panels, battery storage systems, and a grid connection system has been shown to be both economically feasible and technically viable. Energy Management Systems (EMS) reduce peak grid demand and utility demand charges and in this case it was shown to reduce peak grid demand by 66.7%. The battery in this system operated well and safely within the battery's State of Charge (SoC) limits, showing that the system has been sized well to manage and balance the daily load fluctuations without compromising the battery's life. The system was also found to be economically stable and achieved a Levelized Cost of Energy (LCOE) of $0.024/kWh. Regarding grid export and PV contribution, the system was found to reduce the annual grid cost to $60,839.74. The system also provided evidence that local generation and storage offers the ability to reduce reliance on the grid and provide support in charging of hybrid EVs. The hybrid system also provided evidence that supports the added and safe balance of peak demand on the grid.

Future Work

Building upon the state-of-the-art identified in Section 2, our future research will focus on replacing the current rule-based EMS with advanced, intelligent control architectures to further enhance performance:

1. **Predictive Control with Machine Learning:** We will develop a predictive controller utilizing Long Short-Term

Memory (LSTM) networks to forecast short-term EV load demand and PV generation. This will enable pre-emptive battery scheduling, moving from a reactive to a proactive EMS strategy.

2. **Metaheuristic-Optimized Fuzzy Controllers:** Directly inspired by the significant performance gains reported , we will design and implement a Fuzzy Logic Controller optimized by algorithms such as the Sea Horse Optimizer (SHO) or Manta Ray Foraging Optimization (MRFO). The objective will be to achieve the additional 40% reduction in grid dependency hinted at by the integration of controlled storage in that study.
3. **Adaptive Control (MRAC):** We will investigate the application of a TID-MRAC framework for the EV charging station context. This adaptive approach would allow the EMS to dynamically tune its parameters in response to system nonlinearities and component degradation, ensuring robust long-term performance.
4. **Co-optimization of Stationary BESS and V2G:** Future work will explore a hybrid model combining the dedicated stationary BESS with opportunistic V2G support from parked EVs, creating a multi-tiered energy reserve to maximize both peak shaving capability and economic return.

Author Contribution Statement

All authors contributed equally to the study conception and design. Material preparation, data collection, and analysis were performed by the authors. The first draft of the manuscript was written by the authors, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Ethics Approval and Consent to Participate

This study did not involve human participants or animals. Therefore, ethical approval and consent to participate are not applicable.

Consent for Publication

Not applicable.

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Disclosure Statement

The authors declare that they have no competing interests.

References

[1] N. Ebenezer *et al.*, "Electromobility in the global south: An equitable transition toward road passenger transport decarbonization," 2021.

[2] P. Kumar *et al.*, "A comprehensive review of vehicle-to-grid integration in electric vehicles: Powering the future," *Energy Conversion and Management: X*, vol. 25, p. 100864, 2025.

[3] R. Serrano, A. Sultana, D. Kavanaugh, and H. Wang, "Increasing electric vehicle charger availability with a mobile, self-contained charging station," *Sustainability*, vol. 17, no. 6, p. 2767, 2025.

[4] M. S. Mastoi *et al.*, "A study of charging-dispatch strategies and vehicle-to-grid technologies for electric vehicles in distribution networks," *Energy Reports*, vol. 9, p. 1777–1806, 2023.

[5] M. M. Rana, M. Atef, M. R. Sarkar, M. Uddin, and G. M. Shafiullah, "A review on peak load shaving in microgrid—Potential benefits, challenges, and future trend," *Energies*, vol. 15, no. 6, p. 2278, 2022.

[6] X. Tian, B. Yuan, and P. Zheng, "Tri-objective enhanced ISODATA: A synergistic framework of cluster core optimization, inter-class divergence maximization, and adaptive threshold control for smart grid load profiling," *Electric Power Systems Research*, vol. 247, p. 111774, 2025.

[7] J. A. L. Vilaplana, G. Yang, and E. Ackom, "From investment to net benefits: A review of guidelines and methodologies for cost–benefit analysis in the electricity sector," *Energy Research & Social Science*, vol. 124, p. 104052, 2025.

[8] M. Abdelsattar, A. Mesalam, A. Fawzi, and I. Hamdan, "Optimal design and analyzing the techno-economic-environmental viability for different configurations of an autonomous hybrid power system," *Electrical Engineering*, vol. 106, no. 4, p. 4747–4764, 2024.

[9] A. A. Z. Diab, H. M. Sultan, I. S. Mohamed, O. N. Kuznetsov, and T. D. Do, "Application of different optimization algorithms for optimal sizing of PV/wind/diesel/battery storage stand-alone hybrid microgrid," *IEEE Access*, vol. 7, p. 119223–119245, 2019.

[10] Å. L. Sørensen, M. C. Westad, B. M. Delgado, and K. B. Lindberg, "Stochastic load profile generator for residential EV charging," *E3S Web of Conferences*, vol. 362, p. 03005, 2022.

[11] A. H. A. Elkasem, M. Khamies, M. H. Hassan, L. Nasrat, and S. Kamel, "Utilizing controlled plug-in electric vehicles to improve hybrid power grid frequency regulation considering high renewable energy penetration," *Int. J. Electr. Power Energy Syst.*, vol. 152, p. 109251, 2023.

[12] A. H. A. Elkasem, M. Khamies, M. H. Hassan, A. M. Agwa, and S. Kamel, "Optimal design of TD-TI controller for LFC considering renewables penetration by an improved chaos game optimizer," *Journal of Energy Storage*, vol. 72, p. 108960, 2023.

[13] M. A. Attia, M. H. Hassan, S. Kamel, and M. Khamies, "Optimized frequency stabilization in hybrid renewable power grids with integrated energy storage systems using a modified fuzzy-TID controller," *Scientific Reports*, vol. 15, no. 1, p. 20095, 2025.

[14] H. M. Hasanien and A. A. El-Fergany, "Salp swarm algorithm-based optimal load frequency control of hybrid renewable power systems with communication delay and excitation cross-coupling effect," *Electric Power Systems Research*, vol. 176, p. 105938, 2019.

[15] A. H. A. Elkasem, M. Khamies, M. H. Hassan, L. Nasrat, and S. Kamel, "Enhancing power grid frequency stability with an optimized TID-MRAC controller and electric vehicle integration under renewable energy penetration," *Neural Computing and Applications*, vol. 37, p. 19037–19061, 2025.

[16] W. Zhao, Z. Zhang, and L. Wang, "Manta ray foraging optimization: An effective bio-inspired optimizer for engineering applications," *Engineering Applications of Artificial Intelligence*, vol. 87, p. 103300, 2020.

[17] S. Heier, *Grid Integration of Wind Energy Conversion Systems*. New York, NY, USA: Wiley, 1998.

[18] W. Kempton and J. Tomić, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources*, vol. 144, no. 1, p. 280–294, 2005.