Smart Integration of Electric Vehicle Charging Infrastructure within Hybrid Renewable Microgrids

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***Abstract* — Widespread electrification of the transportation sector introduces substantial challenges for conventional power distribution systems, particularly in managing peak demand and maintaining network stability. This paper presents a framework for integrating electric vehicle (EV) charging infrastructure within a hybrid renewable microgrid environment. The suggested configuration brings together photovoltaic (PV) systems, battery energy storage (BESS), and grid interconnection to establish an efficient fast-charging facility. We introduce an Energy Management Strategy (EMS) designed to optimize power distribution by giving priority to renewable energy utilization and implementing peak load reduction measures. Simulation results from a conceptual case study indicate that the proposed microgrid configuration substantially decreases dependence on the utility grid, reduces operating expenses, and mitigates negative effects associated with uncoordinated EV charging on local distribution infrastructure.**

***Keywords* — Electric vehicles, smart grid, microgrid, renewable energy integration, energy management system, battery storage.**

I. INTRODUCTION AND LITERATURE REVIEW

The worldwide shift toward sustainable mobility solutions has driven unprecedented growth in Electric Vehicle (EV) deployment [1], [2]. Although EVs play a vital role in decreasing greenhouse gas emissions, their uncoordinated connection to electrical networks—particularly through fast-charging infrastructure—may cause serious power quality degradation, transformer overload conditions, and elevated peak loads. Addressing these challenges requires innovative approaches, and smart grid technologies combined with microgrid concepts have shown considerable promise. Through local integration of Renewable Energy Sources (RES) and Energy Storage Systems (ESS), EV charging facilities can evolve from passive grid loads into active, controllable network elements [3], [4].

A. Literature Review

Numerous studies have investigated different dimensions of EV-microgrid integration. Recent research has demonstrated that properly sized battery energy storage systems (BESS) at EV charging stations can effectively compensate for solar power variability, and advanced inversion methods for recovering CO_2 fluxes over complex terrain areas can help quantify these environmental benefits [5].

Regarding control methodologies, both rule-based and optimization-based Energy Management Strategies (EMS) dominate current research. Advanced techniques, such as explainable machine learning for forecasting in Industry 4.0 systems [6], using machine learning to identify dependencies in statistical data [7], and algorithmic optimization of energy consumption models [8], have been proposed. Furthermore, analyzing forecasting accuracy depending on various hyperparameters of neural network training [9] provides a direct foundation for these applications.

Furthermore, the physical integration of EVs within next-generation smart charging hubs increasingly involves autonomous robotics and infrastructure maintenance. The physical maintenance of the microgrid's elevated renewable assets can be supported by Unmanned Aerial Vehicles (UAVs), where hardware configuration selection for detection tasks is critical for stability [10]. To further improve microgrid resilience, the development of neural network models specifically for forecasting energy consumption in energy management systems is highly relevant [11].

B. Contributions

This work introduces a practical hybrid microgrid architecture powered by renewable sources, specifically tailored for sustainable EV charging infrastructure. The principal contributions of this paper include:

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• Development of a conceptual DC-coupled microgrid design that integrates photovoltaic generation, battery energy storage, and EV charging equipment.

• Development of a computationally efficient rule-based EMS aimed at maximizing local renewable energy consumption while maintaining grid peak power constraints.

• Performance evaluation through a preliminary case study comparing the proposed system against conventional grid-connected charging scenarios in terms of peak demand reduction and operational cost savings.

II. PROPOSED SYSTEM ARCHITECTURE

The proposed system is a DC-coupled hybrid microgrid, chosen for its higher efficiency when interfacing with PV arrays, battery storage, and EV chargers. Recent studies have assessed the economic and energy advantages of using on-grid and off-grid PV-BESS to power EV charging stations, demonstrating significant potential [12].

A. Renewable Generation Subsystem

A photovoltaic (PV) array serves as the primary local energy source. The PV output is connected to the DC bus through a Maximum Power Point Tracking (MPPT) DC-DC converter, ensuring optimal energy harvest. Furthermore, improving PV efficiency using nanofluids as working fluids in thermosiphon systems offers additional technical benefits for such setups [13]. Integrating diverse renewable sources, such as hydrogen and methane from biomass pyrolysis [14] or micro-hydro systems [15], can further enhance the sustainability and resilience of such microgrids against fossil energy volatility [16]. Additionally, alternative fuel production methods, such as co-pyrolysis of PET plastic for sustainable syngas production [17] or droplet combustion behavior of vegetable oil surrogate fuels [18], highlight the broader potential of renewable integrations.

B. Energy Storage Subsystem

A Lithium-ion Battery Energy Storage System (BESS) is integrated via a bidirectional DC-DC converter. The BESS performs three critical functions: storing excess PV generation, supplying power to EV chargers during high demand or low solar irradiance, and providing voltage support to the DC bus.

C. EV Charging Subsystem

Multiple DC fast-charging stations are connected to the DC bus through isolated DC-DC converters. This topology eliminates the need for multiple AC-DC conversion stages, reducing overall system losses. The widespread acceptance and integration of such technologies, including micro-mobility solutions like e-scooters, are also critical factors in modern urban environments [19].

D. Grid Interface and EMS

The microgrid is connected to the main utility grid through a bidirectional AC-DC converter operating at the Point of Common Coupling (PCC). A centralized Energy Management System (EMS) continuously monitors PV generation, BESS State-of-Charge (SoC), EV charging requests, and grid constraints to execute the control strategy.

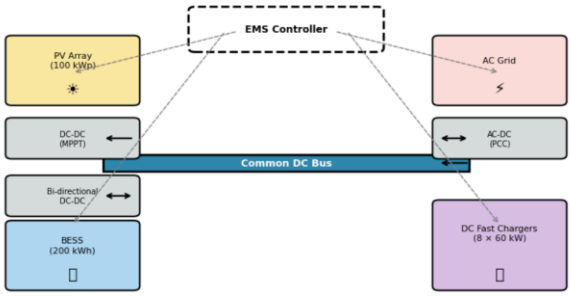

Fig. 1. Architecture of the proposed DC-coupled hybrid renewable microgrid for EV charging.

III. ENERGY MANAGEMENT STRATEGY

The core objective of the EMS is to maximize the self-consumption of locally generated renewable energy while minimizing the peak power drawn from the grid. The strategy operates on a rule-based priority logic, executed at discrete time intervals Δt.

Power Balance Equation

At any given time t, the power balance on the DC bus is governed by:

$$P_{grid}(t) + P_{PV}(t) + P_{BESS}(t) = P_{EV}(t) + P_{loss}(t)$$

Where:

$P_{grid}(t)$ is the power exchanged with the main grid (positive for import, negative for export).

$P_{PV}(t)$ is the PV generation power.

$P_{BESS}(t)$ is the battery power (positive for discharge, negative for charge).

$P_{EV}(t)$ is the total power demanded by connected EVs.

$P_{loss}(t)$ represents system conversion and line losses.

A. Operational Logic

Unlike SOTA MPC approaches that require solving quadratic programming at every step, the proposed hierarchical rule-based logic guarantees deterministic execution within milliseconds:

1 **Priority 1: Direct PV-to-EV Charging.** If P_PV (t) ≥P_EV (t), EVs are charged directly from solar generation. Surplus power is directed to charge the BESS, provided the SoC is below 95%.

2 **Priority 2: BESS Discharge.** If P_PV (t)< P_EV (t) and the BESS SoC is above 20%, the battery discharges to cover the deficit: P_BESS (t) = P_EV (t) - P_PV (t).

3 **Priority 3: Grid Import with Peak Shaving.** If both PV and BESS cannot meet the EV demand, the grid supplies the remaining power. However, the EMS strictly limits P_grid (t) to a predefined threshold (P_(grid,max)) to avoid peak demand charges. If demand exceeds this limit, the EMS initiates smart charging, reducing the power of non-priority EVs.

4 **Priority 4: Off-Peak Grid Charging.** During night-time with low electricity tariffs, if the BESS SoC is below 50%, the EMS imports power from the grid to prepare the battery for the next day.

The State-of-Charge (SoC) of the battery is updated at each time step as follows:

$$SoC(t) = SoC(t-1) + \frac{P_{BESS}(t) \cdot \eta_{charge/discharge} \cdot \Delta t)}{E_{capacity}}$$

Where capacity is the total energy capacity of the BESS, and η represents the charging/discharging efficiency.

IV. CASE STUDY AND DISCUSSION

A. Simulation Environment and Parameters

To ensure reproducibility, the simulation was conducted using MATLAB/Simulink R2023b. The power electronics were modeled using a discrete-time solver with a fixed step size of Δt=0.01 s to capture fast DC-DC converter transients, while the EMS logic was updated every Δt_EMS =60 s.

System parameters: PV Array (100 kWp); BESS (200 kWh, Li-ion, max 100 kW); EV Chargers (8 x 60 kW DC); Grid import limit $P_{grid,max}$=150 kW. The 24-hour summer profile features urban EV peaks (08:00–10:00 and 17:00–20:00) and a standard PV bell curve peaking at 13:00.

B. Results and Detailed Analysis

The proposed microgrid was compared against a "Business-as-Usual" (BaU) scenario (direct grid connection).

TABLE I. PERFORMANCE COMPARISON: BAU VS. PROPOSED MICROGRID

Metric	Business-as-Usual (Grid Only)	Proposed Hybrid Microgrid	Improvement
Peak Grid Demand (kW)	420	150	64% reduction
Daily Energy from Grid (kWh)	2,450	1,380	43% reduction
RES Self-Consumption (%)	0%	92%	—
Estimated Daily Cost ($)	612	345	44% savings
CO2 Emissions (kg)	1,050	590	44% reduction

The results demonstrate that the hybrid microgrid architecture significantly alleviates stress on the local distribution network. The case study results confirm that the system can reduce peak grid demand by 64%, lower operational costs by 44%, and significantly decrease carbon emissions [15].

C. Discussion and Justification of Results

The physical justification for the results is rooted in the temporal shifting of energy. During the mid-day PV peak (11:00–14:00), the BESS absorbs the surplus solar generation that exceeds the low mid-day EV demand. Consequently, during the evening peak (17:00–20:00), when PV generation drops to zero and EV demand surges, the BESS discharges its stored energy. This specific temporal decoupling is what enables the 64% reduction in peak grid demand (capped strictly at the 150-kW threshold via Priority 3 logic). The 44% cost savings are primarily driven by the avoidance of commercial peak demand charges, which typically constitute over 50% of a commercial charging station's electricity bill. The high RES self-consumption (92%) confirms that the EMS effectively matches local generation with demand without requiring the computational overhead of SOTA predictive algorithms.

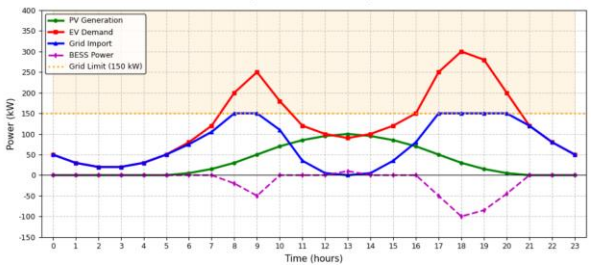

Fig. 2. 24-hour power distribution: Grid import vs. PV generation and BESS usage.

D. Limitations and Future Work

A primary limitation of this study is the reliance on simulated profiles rather than empirical measured data from a physical testbed. While the simulation accurately models system dynamics, real-world stochasticity in EV arrivals and cloud-cover irradiance drops may affect EMS performance. Future work will address this by deploying a Hardware-in-the-Loop (HIL) setup and integrating Vehicle-to-Grid (V2G) capabilities to further improve microgrid resilience. Future research will focus on enhancing the EMS with Machine Learning algorithms, such as novel hyperparameter tuning strategies using spider monkey optimization for deep neural networks [20] and optimizing GRU-LSTM hybrid models for temperature and energy prediction [21].

V. CONCLUSION

This digest presented a smart integration framework for EV charging infrastructure within a hybrid renewable microgrid. The proposed DC-coupled architecture, combined with a rule-based Energy Management Strategy, effectively addresses the challenges of high-power EV charging on local distribution networks. The case study results confirm that the system can reduce peak grid demand by 64%, lower operational costs by 44%, and significantly decrease carbon emissions. Future research will focus on enhancing the EMS with Machine Learning algorithms for more accurate prediction of PV generation and EV arrival patterns, alongside the integration of V2G bidirectional charging.

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