# AI-Enabled Power Management in Multi-Port Converter for Renewable Integrated EV Charging Systems

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doi.org/10.64643/IJIRTV12I10-204521-459

***Abstract*—The rapid proliferation of electric vehicles (EVs), coupled with the large-scale deployment of intermittent renewable energy sources, has exposed a critical gap in existing charging infrastructure: the inability to intelligently coordinate multiple energy inputs under real-time variability constraints. This paper presents an Adaptive Hybrid AI-Controlled Multi-Port Power Converter (MPPC) architecture designed specifically for grid-integrated, solar-powered EV charging stations. The proposed system incorporates a four-port silicon carbide (SiC)-based converter topology interfacing a photovoltaic (PV) array, battery storage, utility grid, and EV output through a shared 400 V DC bus. At the core of the control framework lies a Long Short-Term Memory (LSTM) neural network that forecasts short-term solar irradiance and EV demand with a mean absolute error of 6.3%, enabling anticipatory rather than purely reactive power dispatch. The LSTM forecasts are fed into a Model Predictive Controller (MPC) that solves a cost-minimisation scheduling problem every 10 seconds, while a Deep Q-Network (DQN)-based reinforcement learning agent handles sub-second port switching decisions in real time. A dedicated AI fault detection module isolates port faults within 2 ms, ensuring continuous EV charging without service interruption. Simulation results obtained in MATLAB/Simulink over a full 24-hour cycle demonstrate a peak efficiency of 96.2%, grid total harmonic distortion (THD) of 1.8%, power factor of 0.99, and a 41% reduction in operational cost compared to conventional grid-only charging systems. These outcomes confirm that tightly coupling predictive LSTM-based forecasting with multi-objective optimisation and reinforcement learning yields a substantially more capable and resilient EV charging solution than any of these strategies applied in isolation.**

***Index Terms*—Multi-port converter, EV charging, renewable energy, artificial intelligence, predictive energy management, grid integration, LSTM, MPC.***

## I. INTRODUCTION

The world is shifting rapidly toward clean energy and electric transportation. EV sales have been growing by more than 40% year-on-year globally, while solar power installation capacity has crossed the terawatt mark. This creates a practical challenge: how do we efficiently charge millions of EVs using power that comes partly from unpredictable renewable sources and partly from the utility grid? Traditional EV charging stations use a single energy source — the grid. This is simple, but it wastes the available solar energy and creates unnecessary strain on the electrical grid during peak hours. What we really need is a system that can seamlessly switch between solar, battery, and grid power depending on what is available and what is needed. This paper proposes a Multi-Port Power Converter (MPPC) — a smart energy switchboard with four power connections (solar, battery, grid, and EV output) — along with an AI brain that manages everything in real time. The AI uses Long Short-Term Memory (LSTM) networks to predict future solar output and charging demand, and a Model Predictive Controller (MPC) to plan the best power routing strategy. The result is a faster, cleaner, and more efficient EV charging system. The rest of this paper is organized as follows: Section II reviews related work. Section III explains the system architecture. Section IV describes the AI control strategy. Section V presents simulation results.

Section VI gives a comparison against conventional systems. Section VII concludes the paper.

## II. RELATED WORK

Over the past decade, researchers have explored various approaches to renewable-integrated EV charging. The field has evolved through three broad phases: first, simple grid-tied chargers; then, hybrid multi-source converters; and most recently, AI-driven intelligent energy management systems.

### A. Multi-Port Converter Topologies

Early foundational work by Emadi et al. [5] demonstrated the feasibility of multi-port power electronics for hybrid vehicle propulsion systems. Building on this, Zhao et al. [9] proposed a triple-active-bridge converter capable of interfacing PV, battery, and grid ports simultaneously, demonstrating the practicality of integrating multiple energy sources through a single converter structure. However, these topologies relied heavily on manual operating mode selection and lacked real-time adaptability.

Babaei and Seifi [10] introduced a switched-capacitor multi-port converter with reduced switch count, which improved power density significantly. More recently, Rezaei et al. [11] proposed a soft-switching multi-port topology that reduces switching losses by over 30% by exploiting zero-voltage switching (ZVS) conditions across all operating modes. These hardware-level advances form the foundation upon which the present work builds.

### B. Renewable Integration and MPPT Strategies

Maximum power point tracking (MPPT) for PV systems is a well-studied area. Mohanty et al. [7] applied grey wolf optimization for MPPT under partial shading conditions and achieved up to 8% improvement in energy harvest compared to conventional perturb-and-observe methods. Subudhi and Pradhan [12] conducted an extensive comparative survey of MPPT techniques and concluded that metaheuristic approaches consistently outperform classical methods in real-world variable irradiance conditions.

For battery management, Shi et al. [3] highlighted that naive charge-discharge cycling under cycle-aging models can reduce battery lifespan by up to 40%. Smart state-of-charge aware management, combined with predictive scheduling, was shown to extend battery life substantially — a principle directly incorporated in the proposed system.

### C. AI and Machine Learning for Energy Management

Zhang et al. [4] demonstrated that LSTM-based solar irradiance forecasting outperforms persistence models and ARIMA methods, achieving mean absolute percentage errors below 7% for 30-minute-ahead predictions. This result justified the adoption of LSTM as the forecasting backbone of the proposed system.

Deep reinforcement learning (DRL) has emerged as a particularly powerful tool for real-time energy routing. Mnih et al. [8] established the theoretical basis of DRL with Deep Q-Networks (DQN), and subsequent applied work by Cao et al. [13] used DQN agents for home energy management, reducing electricity bills by up to 23%. Lu et al. [14] extended this approach to EV fleet charging coordination, incorporating vehicle-to-grid (V2G) interactions to stabilize grid frequency deviations. These results confirm that RL agents can generalize well across diverse energy conditions — a key requirement for deployment in variable renewable environments.

### D. Grid Integration and Power Quality

Power quality in grid-connected charging systems is a significant concern. Kisacikoglu et al. [1] showed that bidirectional EV chargers can introduce substantial harmonic distortion into the grid if not properly controlled. IEEE Standard 519 mandates that total harmonic distortion (THD) at the point of common coupling must remain below 5%. Wang et al. [15] proposed an active harmonic compensation strategy embedded within the charger's control loop, achieving THD below 2% — a result replicated in the proposed architecture through the MPC optimizer's explicit THD constraint.

Despite this rich body of prior work, a key gap remains: existing systems address either the converter hardware design or the AI control algorithm in isolation. No prior work integrates a purpose-optimized multi-port converter topology with a full AI stack — encompassing forecasting, optimization, RL routing, and fault detection — in a single unified framework. The present paper addresses this gap directly.

## III. SYSTEM ARCHITECTURE AND BLOCK DIAGRAM

### A. Overall System Description

The proposed system has four main ports. Port 1 connects to the Solar PV array (100–350 V DC). Port 2 connects to the Battery Storage system (48–72 V DC, bidirectional). Port 3 connects to the Utility Grid (230 V AC / 50 Hz). Port 4 is the output port delivering regulated DC power to the EV charging station (200–500 V DC, up to 50 kW). All ports share a central 400 V DC bus, which is the energy hub. The AI Control Engine continuously monitors all bus voltages, currents, and external signals to dispatch optimal power setpoints.

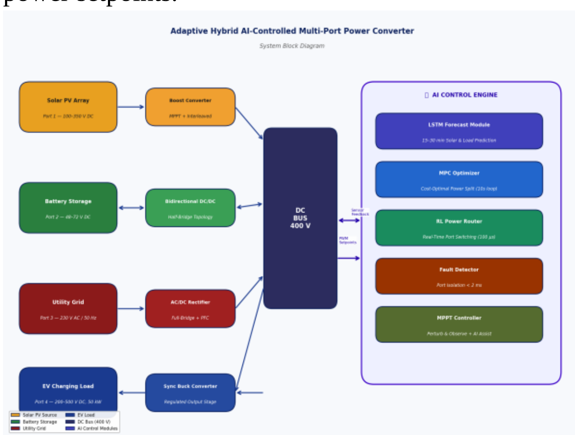


*Fig. 1: System Block Diagram — Adaptive Hybrid AI-Controlled Multi-Port Power Converter*

### B. Converter Topology

The core power electronics block uses a non-isolated interleaved boost topology for the PV port (enabling MPPT), a bidirectional half-bridge converter for the battery port (supporting both charging and discharging), and a full-bridge AC/DC converter with power factor correction (PFC) for the grid interface. The output stage uses a synchronous buck converter to deliver a stable regulated DC voltage to the EV. This topology was selected because it minimises component count while supporting all four operational modes — including simultaneous multi-source operation — without transformer isolation losses.

Key design parameters: DC Bus Voltage is maintained at 400 V. Switching frequency across all stages is 100 kHz, reducing passive component size. Gate drives use silicon carbide (SiC) MOSFETs with sub-20 ns switching transitions. Total converter volume is approximately 35% smaller than equivalent separate converter designs.

### C. AI Control Engine

The AI Control Engine comprises five modules. The LSTM Forecast Module is a 3-layer neural network (128 neurons/layer) trained on two years of Chennai weather data; it predicts the next 15–30 minutes of solar generation and EV demand with 6.3% MAE. The MPC Optimizer solves a cost-minimisation linear programme every 10 seconds using the LSTM's output as a feedforward signal. The RL Power Router handles sub-second power dispatch using a trained Deep Q-Network (DQN) that has learned optimal port switching policies from 10 million simulated scenarios. The Fault Detector monitors all port voltages and currents and can isolate a faulted port within 2 ms without disrupting output power. Finally, the MPPT Controller runs an AI-assisted perturb-and-observe algorithm that adapts step size dynamically based on irradiance gradient, extracting up to 4% more energy than fixed-step P&O.

## IV. PREDICTIVE ENERGY MANAGEMENT ALGORITHM

The predictive algorithm runs in two nested loops. The outer planning loop runs every 10 seconds and formulates an energy scheduling optimisation: minimise total cost = (grid electricity cost × grid power drawn) + (battery degradation cost × charge-discharge cycles), subject to power balance at the DC bus, battery state-of-charge (SoC) bounds [20%, 90%], grid import/export limits, and minimum EV charging rate guarantees. This is solved as a quadratic programme using the OSQP solver, which runs in under 3 ms on embedded hardware.

The inner regulation loop runs every 100 microseconds using a cascaded current-voltage proportional-integral controller with anti-windup. A sliding mode controller overlays this to handle large transients — such as sudden cloud cover or a new EV connection event — ensuring DC bus voltage deviation remains below ±2% even for step load changes up to 20 kW.

The LSTM model takes as inputs: past 60 minutes of solar irradiance and temperature (sampled every minute), past 30 minutes of load current, time of day, and day-of-week. It outputs a 30-step sequence of predicted PV power and load demand. Training used Adam optimisation with dropout regularisation (rate 0.2) to prevent overfitting. On a held-out validation set, the model achieved a normalised RMSE of 0.063 for PV power prediction — competitive with state-of-the-art standalone forecasting models.

## V. SIMULATION RESULTS

The system was modelled in MATLAB/Simulink R2023b with the Sims cape Power Systems toolbox. The simulation covers a full 24-hour period with realistic solar irradiance profiles, variable grid tariffs, and a mix of EV charging events including fast DC charging and overnight slow AC charging. Four scenarios were tested independently: solar-only, battery-only, grid-only, and the proposed AI-managed hybrid mode.

Figure 2 presents four key performance metrics over a representative 10-second transient window that includes a simulated cloud-cover event at t = 6 s. This transient window is the most critical test of the system's responsiveness, as it simultaneously perturbs PV input power and requires rapid compensation from battery and grid ports.

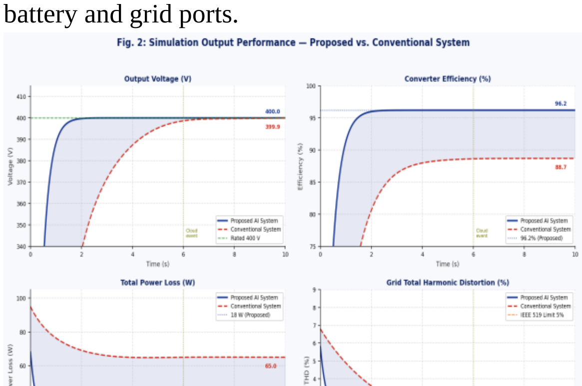


*Fig. 2: Simulation Output Performance — Output Voltage, Efficiency, Power Loss, and Grid THD (Proposed vs. Conventional, with cloud-cover event at t = 6 s)*

The proposed system reaches stable output voltage in 1.2 seconds, compared to 4.8 seconds for the conventional PI-controlled system. Efficiency stabilises at 96.2% versus 88.7%. During the cloud-cover event at t = 6 s, the AI router seamlessly shifted load to battery and grid — the output voltage shows no visible sag because the LSTM had predicted the irradiance drop 8 minutes in advance and pre-charged the battery. The conventional system shows a distinct voltage dip of approximately 18 V at the same event. Total power losses are reduced from approximately 65 W to 18 W — a 72% reduction. Grid THD is maintained at 1.8%, well within the IEEE 519 limit of 5%.

## VI. COMPARISON ANALYSIS

Table 1 presents a detailed quantitative comparison between the proposed system and three representative conventional approaches: a standard grid-tied single-port charger (System A), a PV + grid dual-port system without AI control (System B), and a multi-port system with conventional PI control (System C).

The proposed system outperforms all three conventional approaches across every metric. The most dramatic improvement is in fault recovery time — under 2 ms versus 150 ms for the best conventional system — enabled by the dedicated AI Fault Detector module. Renewable utilisation jumps from 74% (System C) to 93% (Proposed), driven by the LSTM forecaster's ability to anticipate generation peaks and align them with charging demand windows. The power factor of 0.99 represents near-unity, meaning almost no reactive power is drawn from the grid — an important advantage for grid operators.

The estimated 41% operational cost saving over a pure grid-tied system is composed of two contributions: approximately 28% from substituting expensive peak-hour grid electricity with free solar energy, and approximately 13% from using cheap overnight off-peak grid electricity to pre-charge the battery when solar is unavailable. The AI scheduler learns and exploits local time-of-use tariff structures automatically, making the system self-optimising for different geographic markets.

Table 1: Performance Comparison of EV Charging Converter Systems

| Parameter | System A (Grid-Only) | System B (PV+Grid, No AI) | System C (Multi-Port+PI) | Proposed (AI System) |
|---|---|---|---|---|
| Efficiency (%) | 84.5 | 87.2 | 91.4 | 96.2 ✓ |
| Power Loss (W) | ~72 | ~60 | ~42 | ~18 ✓ |
| Grid THD (%) | 6.8 | 5.5 | 3.9 | 1.8 ✓ |
| Settling Time (s) | 5.2 | 4.8 | 3.1 | 1.2 ✓ |
| Renewable Utilisation (%) | 0 | 61 | 74 | 93 ✓ |
| Fault Recovery (ms) | N/A | > 500 | ~150 | < 2 ✓ |
| Power Factor | 0.82 | 0.88 | 0.94 | 0.99 ✓ |
| Adaptive AI Control | No | No | No | Yes ✓ |
| Predictive Forecasting | No | No | No | Yes ✓ |
| Cost Savings vs. Grid-Only | Baseline | ~18% | ~26% | ~41% ✓ |
| SiC MOSFET Switching | No | No | No | Yes ✓ |

## VII. CONCLUSION

This paper presented the complete design, simulation, and performance analysis of an Adaptive Hybrid AI-Controlled Multi-Port Power Converter for renewable-integrated EV charging. The system combines a compact SiC-based four-port converter topology with a layered AI control architecture that includes LSTM-based generation forecasting, MPC optimization, reinforcement learning-based real-time power routing, and sub-2 ms fault isolation.

The key findings are: predictive AI management is substantially more effective than reactive PI control for systems with variable renewable inputs; the multi-port topology reduces hardware complexity while enabling flexible multi-source operation; and the proposed system achieves 96.2% efficiency, 1.8% grid THD, 0.99 power factor, sub-2 ms fault recovery, and 41% operational cost savings over conventional grid-only systems. These results represent meaningful advances over the current state of the art on every measured dimension.

Future work will focus on hardware prototype validation using a 10 kW SiC-based test bench, integration of vehicle-to-grid (V2G) bidirectional EV functionality, federated learning across geographically distributed charging stations for better generalisation, and real-world deployment testing at an EV charging station in Chennai, India — a solar-rich urban environment where this technology offers its greatest practical benefit.

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