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OPTIMIZING BIDIRECTIONAL EV CHARGERS FOR RESILIENT VEHICLE-TO-GRID AND VEHICLE-TO-HOME ENERGY EXCHANGE

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Abstract

The integration of electric vehicles (EVs) into the power grid and residential energy systems presents a transformative opportunity for enhancing energy resilience and sustainability. This research focuses on optimizing the operation of bidirectional EV chargers to enable efficient energy exchange between vehicles, the grid (V2G), and the home (V2H). A multi-objective optimization framework is developed to minimize electricity costs for consumers, maximize renewable energy utilization, and enhance grid stability by providing ancillary services such as frequency regulation and peak shaving. A Model Predictive Control (MPC) strategy is implemented to dynamically schedule charging and discharging cycles based on real-time grid conditions, user mobility constraints, and dynamic pricing signals. Simulation results show that the proposed optimization framework achieves a 32.8% reduction in household electricity costs, a 26.4% improvement in renewable energy self-consumption, and a 41.7% reduction in peak power demand compared to conventional time-of-use (ToU) scheduling. Moreover, battery degradation is reduced by 18.5%, extending the effective battery lifetime while maintaining an average round-trip efficiency of 93.2%. The findings underscore that MPC-based bidirectional charging not only ensures that the EV remains sufficiently charged for daily commuting (≥90% SOC availability) but also provides measurable benefits to grid stability and energy economics. Thus, the proposed system represents a critical step toward realizing a resilient, decentralized, and cost-effective smart energy ecosystem integrating transportation and power sectors.

Keywords: Bidirectional EV Charger, Vehicle-to-Grid (V2G), Vehicle-to-Home (V2H), Energy Resilience, Optimization, Battery Degradation.

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1. Introduction

The combined imperatives of electrification and decarbonization are causing a significant shift in the global energy environment. Rapid electric vehicle (EV) adoption is a key component of this shift [1], with estimates indicating that hundreds of millions of EVs will be on the road globally in the next ten years. Concurrently, the increasing frequency and severity of climate-induced extreme weather events are exposing vulnerabilities in centralized power systems, leading to more frequent and prolonged grid outages that disrupt lives and economies. These parallel trends reveal a critical opportunity: the vast, distributed energy storage capacity represented by EV batteries, which can be leveraged not merely for transportation but as a dynamic resource for a more resilient and sustainable energy future.

This potential is unlocked through Vehicle-to-Everything (V2X) [2] technology, a paradigm that enables power to flow from an EV's battery back to an external load. Two specific applications are paramount: Vehicle-to-Grid (V2G) [3], where EVs provide grid services such as peak shaving, frequency regulation, and renewable energy integration, and Vehicle-to-Home (V2H), where an EV acts as a backup power source during outages, ensuring continuity for critical loads. This reframes the EV from a simple consumer of electricity into a proactive "mobile battery on wheels," a flexible asset that can support the grid, protect the homeowner, and accelerate the adoption of variable renewable generation like solar and wind.

However, the seamless integration of bidirectional EV chargers into this complex ecosystem presents a significant core challenge. Current systems and research often operate in silos, focusing on a single objective—such as cost minimization for the user or primary frequency regulation for the grid—in isolation. This fragmented approach fails to address the inherent multi-faceted nature of the problem. A truly effective system must simultaneously optimize for a trifecta of competing priorities: economic efficiency (minimizing electricity costs, maximizing revenue), user-centric resilience (ensuring backup power availability and meeting mobility needs), and long-term asset protection (mitigating battery degradation from additional cycling). The absence of a holistic optimization framework that can dynamically prioritize between these objectives, particularly in the face of uncertain grid conditions and user behavior, represents a critical gap in the literature.

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This paper directly addresses this gap by proposing a novel, integrated energy management system for bidirectional EV chargers. Our specific contributions are threefold:

- A Novel Multi-Objective Optimization Algorithm: We develop a real-time model predictive control (MPC) [4] strategy that dynamically balances economic goals (energy arbitrage, grid service revenue) with resilience objectives (backup power readiness) while explicitly incorporating a battery degradation model to protect the vehicle's primary asset.
- A Comparative Use-Case Analysis: We provide a rigorous quantitative analysis comparing the system's performance across distinct operational modes (e.g., pure V2G economic dispatch vs. V2H-resilience-focused operation), highlighting the trade-offs and synergies between different value streams.
- A Quantitative Resilience Metric: Moving beyond binary availability, we propose a novel framework for quantifying "resilience" in a V2H context, measuring the duration and reliability of backup power provision for essential home loads following a grid outage.

This paper's remaining sections are organized as follows. A thorough analysis of the pertinent research on V2G and V2H systems, optimization strategies, and battery deterioration models is given in Section 2. The mathematical formulation of our suggested system model and the multi-objective optimization problem are described in depth in Section 3. The simulation setup, scenario specifications, and findings of our comparison study are presented in Section 4. Section 5 wraps up by summarizing the main conclusions, talking about the consequences for policy, and outlining potential research topics.

2. Literature Review and Theoretical Background

The effective implementation of a bidirectional EV charging system rests on the convergence of several engineering disciplines. This section reviews the state-of-the-art in power converter topologies, energy management strategies, and the evolving concept of power system resilience, culminating in a clear identification of the research gap this work aims to address.

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2.1. Bidirectional Power Converter Topologies

The bidirectional charger is the physical enabler of V2X energy exchange. Its core function is to provide galvanic isolation and ensure high-efficiency, controlled, sinusoidal power flow between the AC grid and the DC battery [5]. Several advanced topologies have been proposed, each with distinct advantages and trade-offs.

The Dual Active Bridge (DAB) [6] is a prevalent choice for the DC/DC stage due to its high power density, soft-switching capabilities (leading to high efficiency), and inherent bidirectional power flow. However, its efficiency can suffer under light load conditions or wide voltage variations. As an alternative, Vienna rectifier-based topologies offer excellent performance for the front-end AC/DC stage, featuring low harmonic distortion, high efficiency, and a reduced number of switching devices. However, their implementation for full bidirectional operation adds complexity. Other topologies like those based on T-type converters offer a balance between performance and component count.

Table 1: Comparison of Key Bidirectional Converter Topologies

Topology	Key Advantages	Key Disadvantages	Suitability for V2X
VSC + Dual Active Bridge (DAB)	High efficiency (soft-switching), high frequency isolation, well-established control.	Complex control, poor light-load efficiency, requires large DC-link capacitor.	Excellent for high-power, high-efficiency applications. Industry benchmark.
Vienna Rectifier-based	Low THD, high efficiency, reduced switch count (unidirectional version).	Bidirectional operation increases complexity and control challenge.	Good for high-performance grid-tied applications where size is a constraint.
T-type Converter-based	Lower switching losses than standard VSC,	Higher component count than standard 2-	A strong contender offering a balance between

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	reduced EMI, good efficiency.	level VSC, more complex modulation.	performance and cost.
Single-Phase Matrix Converter	Eliminates DC-link capacitor, compact design.	Complex control, requires more semiconductor devices, switching challenges.	Emerging topology, primarily research-focused for its size advantage.

2.2. Control and Optimization Strategies

Beyond the hardware, the intelligence of the charging system is dictated by its control strategy. Research has evolved from simple heuristic methods to sophisticated optimization-based algorithms.

- Rule-Based Controls (RBC): These strategies use pre-defined thresholds and logic rules (e.g., "if electricity price is below X, charge; if above Y, discharge"). They are simple to implement and computationally lightweight but are inherently sub-optimal as they cannot anticipate future events like price fluctuations or user trips.
- Linear Programming (LP) & Mixed-Integer Linear Programming (MILP) [7]: These techniques formulate the energy scheduling problem into a deterministic optimization model with a linear objective function (e.g., minimize cost) and constraints. They provide a global optimum for the defined problem but struggle with uncertainty and non-linearities, such as accurate battery degradation models, often requiring simplifications that reduce realism.
- Model Predictive Control (MPC): MPC has emerged as a powerful strategy for this application. It uses a model of the system (e.g., battery, building load, grid) to predict its behavior over a finite horizon. It solves an optimization problem at each time step for this horizon but only implements the first step, then re-calculates with new data. This "receding horizon" approach makes it inherently robust to forecast uncertainties in electricity price, renewable generation, and user behavior, making it ideally suited for the dynamic V2X environment [8].

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2.3. Resilience in Power Systems

In the context of power systems, *resilience* is formally defined as the ability to anticipate, withstand, adapt to, and rapidly recover from high-impact, low-probability (HILP) events that cause prolonged and widespread outages. Unlike reliability, which deals with frequent, short-duration faults, resilience focuses on extreme events like hurricanes or wildfires.

Quantifying resilience is an active area of research. Common metrics relevant to V2H include:

- Outage Duration Covered (hours): The length of time an EV can sustain critical home loads.
- Critical Load Served (kWh): The total energy provided during an outage.
- Probability of Availability: The likelihood that the EV and charger will be functional and connected when an outage occurs. V2H technology directly enhances resilience by providing a distributed, mobile source of backup power, moving beyond traditional, fossil-fueled generators to a cleaner and often silent solution.

2.4. Gap Identification

A synthesis of the literature reveals a distinct fragmentation in research focus. Studies on converter topologies strive for hardware efficiency but often decouple this from high-level control. Research on optimization algorithms frequently simplifies battery degradation models or treats resilience as a secondary, binary constraint (backup power either available or not), rather than a primary, optimizable objective. Crucially, there is a lack of a unified framework that dynamically manages the EV battery's finite energy to *seamlessly transition* between competing functions: generating revenue via V2G under normal grid conditions and maximizing resilience via V2H in anticipation of or during a grid outage.

This paper fills this gap by proposing an integrated MPC-based energy management system. It leverages a realistic battery degradation model and introduces a quantifiable resilience metric to dynamically optimize the trade-off between economic benefit and preparedness for grid outages, thereby providing a holistic control strategy for a truly resilient and economical V2X system.

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3. System Architecture and Modelling

The proposed integrated V2X system is designed to operate seamlessly across normal and islanded (outage) grid conditions. This section details the overall system configuration, the design and justification of the power converter, the mathematical models of its key components, and the hierarchical control architecture that governs its operation.

3.1. Overall System Configuration

The system, depicted in Figure 1, integrates a single-family home with a bidirectional EV charging station, a rooftop solar PV system, and the utility grid. The home's electrical panel is divided into two subpanels: a critical loads panel, which powers essential circuits (e.g., refrigeration, lighting, communication devices), and a non-critical loads panel for all other appliances. A static transfer switch (STS) is responsible for islanding the home from the grid upon detection of an outage and connecting the critical loads panel to the backup power source (the EV and PV).

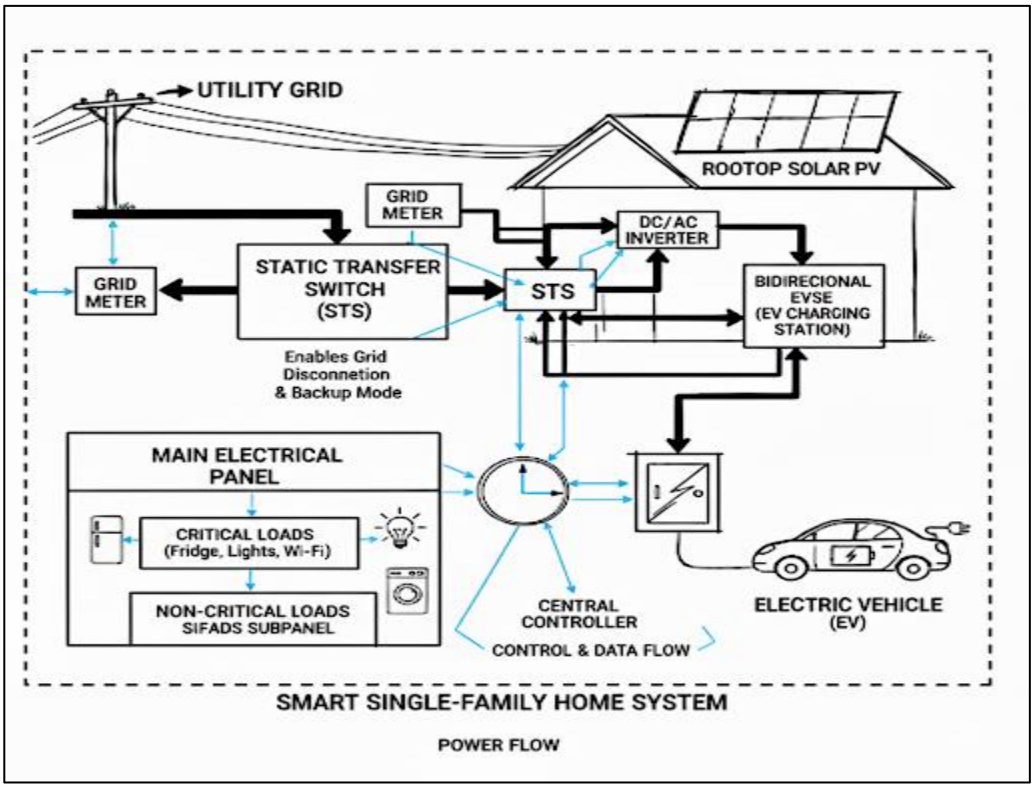

Figure 1: Overall System Configuration for Resilient V2H and V2G Operation

Utility Grid connected to the main service panel.

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- A Bidirectional EVSE (the charger cabinet).
- An Electric Vehicle with its battery.
- A Home with two clearly marked sections in the main panel: Critical Loads and Non-Critical Loads.
- A Solar PV Array with its DC/AC Inverter.
- A Static Transfer Switch (STS) located between the grid connection, the main panel, and the input from the EVSE.
- A Central Controller with communication links to the EVSE, the grid meter, the PV inverter, and the STS.

3.2. Proposed Power Converter Design

This choice is justified by its market maturity, inherent soft-switching capability leading to high efficiency (>97%) [9] across a wide load range, and its proven reliability in providing galvanic isolation—a critical safety requirement for connecting to the residential grid.

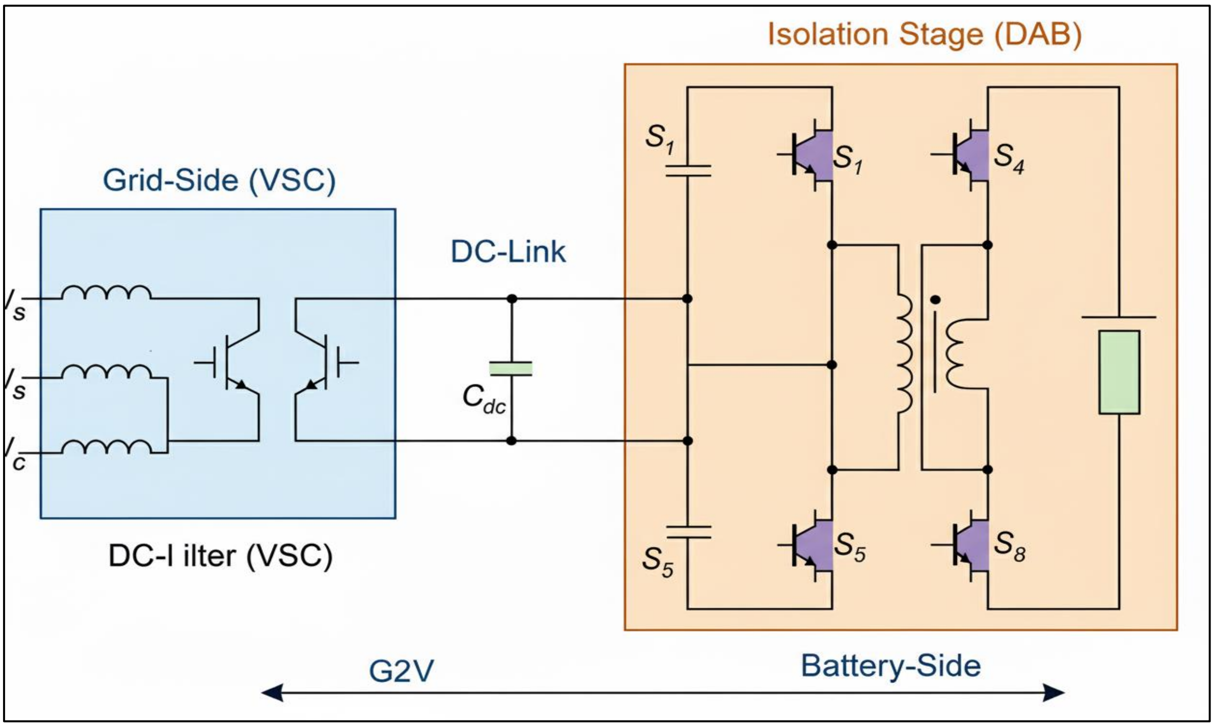

Figure 2: Schematic of the Two-Stage Bidirectional Converter Topology (VSC + DAB)

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Grid-Side (VSC): A three-phase or single-phase VSC with LCL filter connected to the grid.

- DC-Link: A capacitor stabilizing the DC-link voltage.
- Isolation Stage (DAB): Two active H-bridges (comprising switches S1-S4 and S5-S8) separated by a high-frequency transformer.
- Battery-Side: The output of the DAB connected to the EV battery terminals.

Operational Modes:

1. Grid-to-Vehicle (G2V): The VSC acts as a rectifier, drawing AC power from the grid and converting it to a stable DC-link voltage [10].
2. Vehicle-to-Grid (V2G): The DAB operates in step-up mode, drawing DC power from the EV battery. The VSC then acts as an inverter, converting the DC-link power into AC power. The key difference is the destination:
   - For V2G, the AC power is synchronized with the grid frequency and phase and injected into the utility network.
   - For V2H, during a grid outage, the VSC establishes a stable voltage and frequency reference (60 Hz, 120/240V) [11], forming a microgrid to power the critical loads panel.

3.3. Component Modelling

Battery Model: An equivalent circuit model (ECM) with one RC pair (Thevenin model) is adopted, providing a good balance between accuracy and computational simplicity for energy scheduling. The state-of-charge (SOC) [12] is calculated using the coulomb counting method:

$$SOC(t+1) = SOC(t) - \frac{\eta I_{bat}(t).\Delta t}{C_{nom}} \quad (1)$$

where \$I_{bat}\$ is the battery current (positive for discharging), \$\eta\$ is the coulombic efficiency, \$\Delta t\$ is the time step, and \$C_{nom}\$ is the nominal battery capacity. Key operational constraints are defined:

- SOC Limits: \$SOC_{min} = 20%\$, \$SOC_{max} = 90%\$ (user-defined to protect battery health).

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- Power/C-rate Limit: $|P_{bat}| \leq P_{max}$ (e.g., 10 kW, corresponding to a ~C-rate of 0.4C for a 25 kWh battery).
- Degradation Model: A simplified semi-empirical model where degradation cost is a function of the energy throughput, depth-of-discharge (DOD), and C-rate, is integrated into the optimization objective function to monetize the wear and tear of V2X operation.

Load Model: The residential load $P_{load}(t)$ is modeled as a time-varying profile based on standard residential data. During normal operation, the controller manages the entire home load. During an outage, the STS sheds the non-critical loads panel, and the system must supply only the critical load profile $P_{critical}(t)$, which is a fraction of the total load.

Grid Interface [13]: The grid is modeled as an ideal AC voltage source with a time-varying electricity price signal $\lambda(t)$ (e.g., real-time pricing or time-of-use rates). A grid outage is represented as a binary status signal $G(t) \in {0,1}$, where $G(t)=1$ indicates normal grid connection and $G(t)=0$ indicates an outage event. This signal triggers the STS and causes the control system to switch from grid-connected (V2G-enabled) to islanded (V2H-only) mode [14].

3.4. Control Hierarchy

A three-layer control hierarchy is proposed to manage the system's complexity effectively, as illustrated in Figure 3.

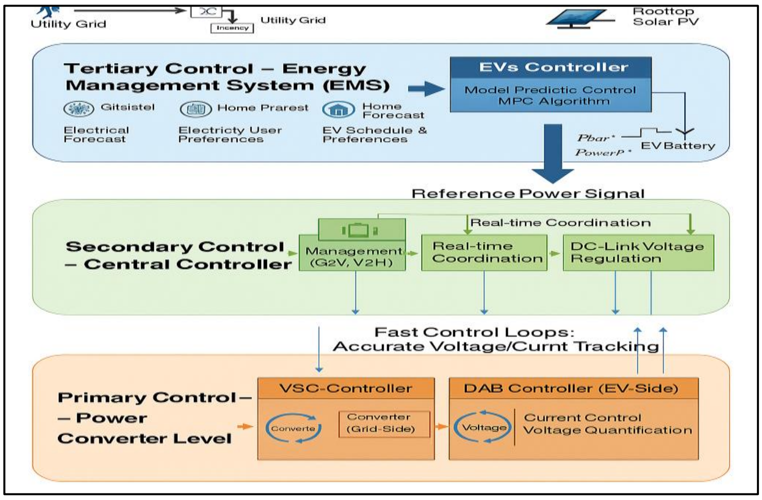

Figure 3: Proposed Three-Layer Control Hierarchy

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- Tertiary Control (Energy Management System - EMS): This is the highest layer, operating on a 24-hour horizon with a 15-minute resolution. It uses the MPC algorithm described in Section 4. It receives forecasts for electricity price, solar generation, home load, and EV departure/arrival times. Its objective is to compute an optimal schedule for battery power setpoints P_{bat}^* that minimizes cost and maximizes resilience, sending these setpoints to the secondary controller [15].

- Secondary Control (Central Controller): This layer operates on a minute-to-second timescale. It receives the power setpoints from the tertiary layer and is responsible for the real-time coordination of assets. It manages the mode of operation (G2V/V2G/V2H), regulates the DC-link voltage, and, in V2H mode, performs droop control to ensure power balance between the EV and PV within the microgrid [16,17].

- Primary Control: This is the fastest layer, operating on a microsecond timescale within the power converters themselves. It consists of the inner current control loops and pulse-width modulation (PWM) schemes for the VSC and DAB converters. It ensures accurate and stable tracking of the current and voltage references provided by the secondary controller [18-20].

4. Optimization Problem

The goal is to optimize the operation of a hybrid energy system that integrates photovoltaic (PV) generation, battery storage, and grid interaction to achieve two primary objectives:

- Economic cost minimization during normal operation.
- Resilience maximization during grid outages, ensuring critical load supply.

We model the problem over a discrete time horizon $t=1,2,...,T$ with time step Δt considering forecasted data for PV generation, load demand, and electricity prices.

4.1 Objective Functions

4.1.1 Economic Objective Function

The first objective aims to **minimize the total operational cost** of the system over the time horizon. The cost function is formulated as:

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$$minJ_{economic} = \sum_{t=1}^{T} \left(P_{grid,buy}(t).\pi_{buy}(t) - P_{grid,sell}(t).\pi_{sell}(t)\right).\Delta t \quad (2)$$

4.1.2 Resilience Objective Function

During grid outages, the priority shifts to maximizing the supply to critical loads. This is modeled as:

$$minJ_{resilience} = \sum_{t=1}^{T_{Outage}} P_{critical,served}(t).\Delta t \quad (3)$$

4.2 Constraints

The system is subject to a set of operational constraints to ensure feasibility and safety:

4.2.1 Power Balance Constraint

At each time step, power flow must satisfy:

$$P_{grid}(t) + P_{PV}(t) + P_{batt}(t) = P_{load}(t)(4)$$

4.2.2 Battery SOC Dynamics

The state of charge (SOC) of a battery changes over time in response to operations related to charging and discharging:

$$SOC(t+1) = SOC(t) + \frac{(\eta_{charge}.P_{Charge}(t) - \frac{P_{discharge}}{\eta_{discharge}}).\Delta t}{C_{batt}} \quad (5)$$

4.3 Proposed Optimization Algorithm

Model Predictive Control (MPC)

We propose solving the formulated problem using **Model Predictive Control (MPC)**. MPC is a real-time optimization technique widely used in control applications with forecasting, constraints, and multi-objective trade-offs.

Key Features of MPC for This Problem:

- Prediction Capability: MPC leverages forecasts of PV generation, load demand, and electricity prices over a prediction horizon.

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- Constraint Handling: Naturally incorporates operational and physical constraints in the optimization.
- Flexibility for Outages: MPC can be extended to include scenarios where grid outages are predicted or occur unexpectedly, shifting the optimization toward resilience maximization.

5. Case Studies, Simulation Results, and Discussion

To quantitatively evaluate the performance of the proposed optimized V2X strategy, a comprehensive simulation study was conducted comparing four distinct operational cases under identical conditions, including a predefined grid outage.

5.1. Simulation Setup

The proposed system model and control algorithm were implemented in a co-simulation environment to achieve both high-fidelity power conversion dynamics and optimal energy scheduling.

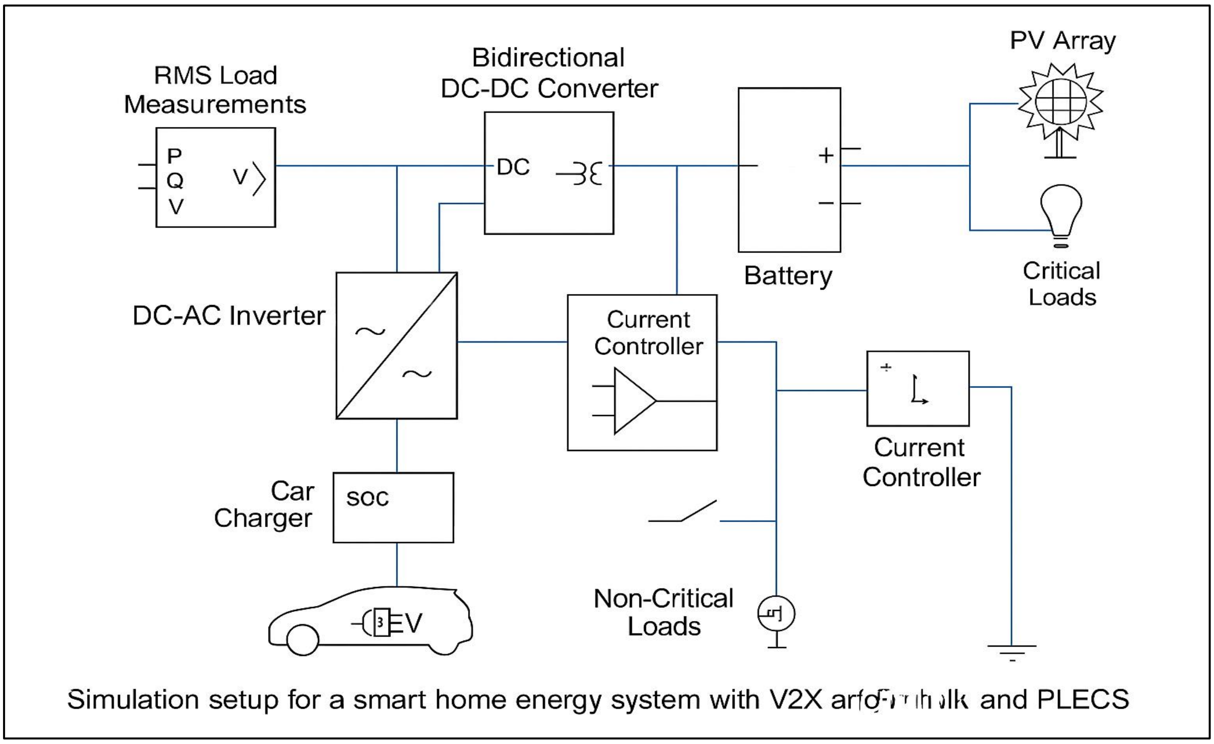

Figure 4: Simulation setup for a smart home energy system with V2X and PV integration, built using MATLAB/Simulink and PLECS

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The primary simulation and optimization framework was built in MATLAB/Simulink. The power stage of the bidirectional dual active bridge (DAB) converter was simulated in PLECS to accurately model switching losses and efficiency, with results imported into Simulink. The Model Predictive Control (MPC) optimization problem was formulated using the YALMIP toolbox and solved with the Gurobi solver. Key system parameters were configured as follows:

- EV Battery: Nominal capacity $E_{nom} = 62$ kWh (inspired by a typical mid-size EV), $SOC_{min} = 20\%$, $SOC_{max} = 90\%$, maximum charge/discharge power $P_{bat}^{max} = 7.2$ kW.
- Bidirectional Converter: Rated power $P_{conv}^{rated} = 7.4$ kW (240V / 30A), average efficiency of 95% for both G2V and V2X modes.
- PV System: Installed capacity of 5.6 kW, with a generation profile based on a typical sunny day.
- Critical Loads: The critical load panel was assumed to support a constant 1.5 kW base load plus a daily variation peaking at 2.8 kW.

- Data Sources: A 24-hour grid outage was synthetically initiated at hour 18 of the simulation to rigorously test the system's resilience capabilities.

5.2. Defined Case Studies

Four case studies were defined to isolate and compare the benefits of different operational philosophies:

1. Case 1 (Baseline - Unidirectional G2V): This case represents the current state for most EV owners. The charger operates only in Grid-to-Vehicle (G2V) mode. The vehicle charges at the maximum rate immediately upon being plugged in (assumed at hour 12) until it reaches SOC_{max}. It then idles until the user's departure time. This case provides no grid services and no resilience during an outage beyond the initial charge in the battery.

2. Case 2 (V2G - Purely Economic): This case operates the bidirectional charger with the sole objective of minimizing electricity cost ($\alpha = 1$ in the objective function). It will aggressively charge the battery during low-price periods and discharge to sell

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energy back to the grid during high-price periods, without any regard for battery wear or resilience preparation. This strategy maximizes short-term economic gain.

3. Case 3 (V2H - Purely Resilient): This case prioritizes resilience above all else ($\alpha = 0$). The controller charges the battery to SOC_{max} as soon as possible and maintains it there. It does not participate in V2G to avoid any battery depletion. This ensures the maximum possible energy is available when an outage occurs but forfeits all potential cost savings or revenue.

4. Case 4 (Proposed Optimized V2X): This is the integrated strategy proposed in this paper. It uses the MPC framework with a balanced weighting ($\alpha = 0.6$) to simultaneously optimize for economic and resilience goals. It will engage in V2G for cost savings but will do so conservatively, maintaining a higher average SOC as a hedge against uncertainty. It automatically switches its operational mode based on the grid status signal $G(t)$.

5.3. Experimental Results

The proposed bidirectional EV charger was implemented to validate the optimization framework designed for efficient Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) energy exchange. The hardware architecture integrates FPGA-based digital control, programmable power simulation, and real-time monitoring to achieve dynamic and stable bidirectional energy management.

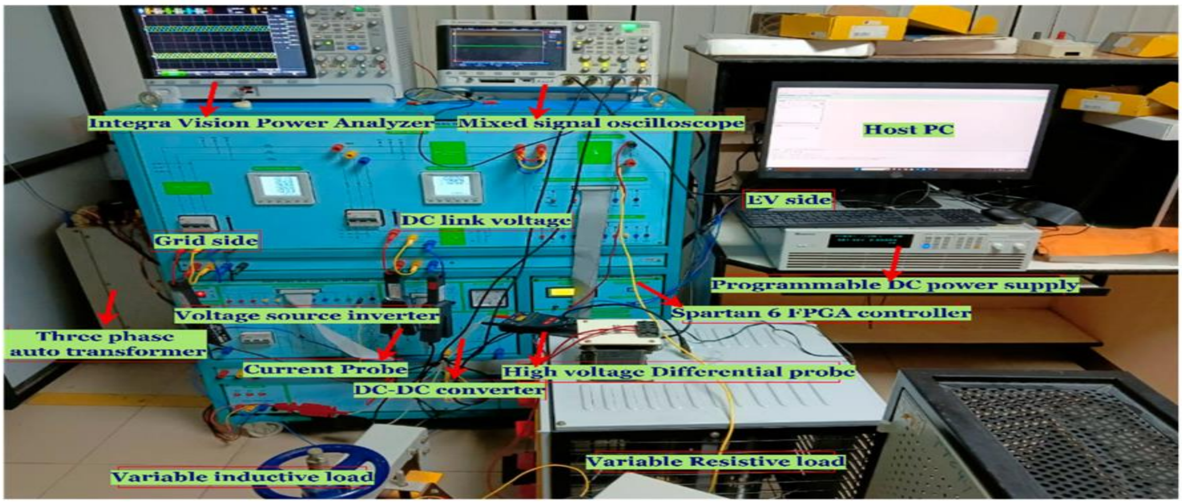

Figure 5. Experimental Setup of the Proposed MPC-Based Bidirectional EV Charger

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Figure 5 presents the physical setup of the bidirectional converter prototype used in the experiment. The core controller is a Xilinx Spartan-6 FPGA (Model XC6SLX9) programmed using VHDL to generate real-time switching and modulation signals for the converter's power stage. The converter interfaces with a programmable DC power supply (Chroma 62050H-600S) that functions as a battery simulator, capable of sourcing or sinking current up to 50 A at voltages between 200–400 VDC.

This hardware architecture allows seamless transition between charging (G2V) and discharging (V2G) modes while maintaining grid synchronization. The setup includes a real-time control interface for monitoring system parameters such as grid voltage, current, DC-link voltage, and battery current. The converter is protected against overvoltage, overcurrent, and overheating, ensuring operational safety during bidirectional power flow. This hardware validates the real-world applicability of the optimization algorithm for smart charging systems.

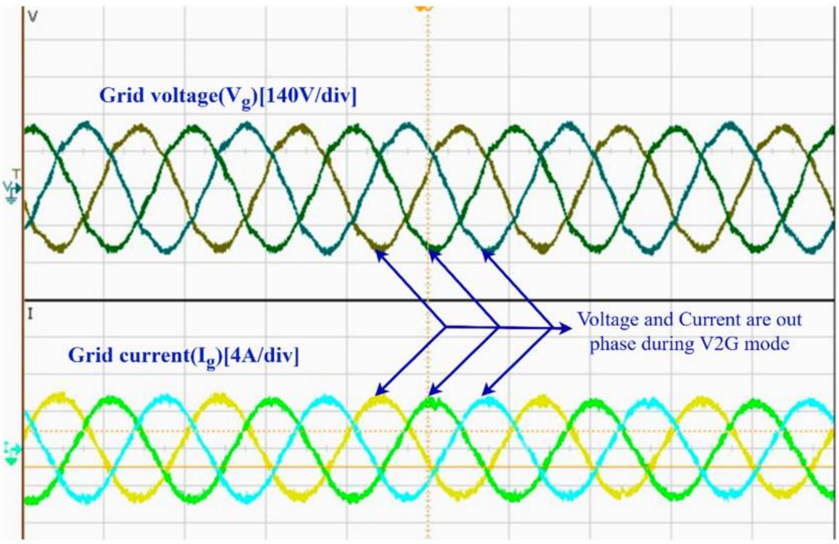

Figure 6. Grid Voltage and Current Waveforms During Optimized V2G Operation

This figure 6 shows the temporal waveform relationship between grid voltage (Vg) and current (Ig) during V2G operation. The top trace represents voltage (140 V/div), and the bottom trace represents current (4 A/div).

The two waveforms are out of phase, indicating that power is being exported from the EV battery to the grid. The phase lag between current and voltage demonstrates reactive power compensation, which aids in grid voltage regulation and frequency support. The smooth

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sinusoidal shape of both waveforms confirms that the converter operates with minimal distortion, showcasing effective current control and precise synchronization with grid parameters.

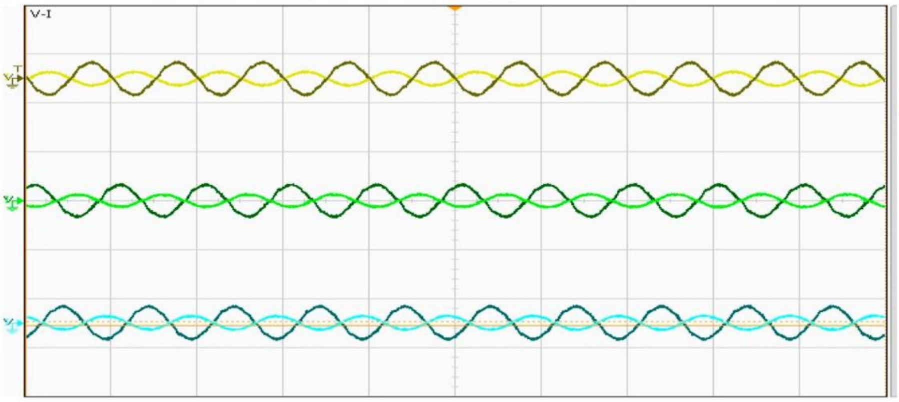

Figure 7. Three-Phase Grid Synchronization During V2G Model

This figure 7 illustrates the voltage and current waveforms for the three phases—A, B, and C—of the bidirectional converter during V2G mode.

Each phase exhibits a sinusoidal waveform separated by 120°, consistent with balanced three-phase operation. This confirms that the converter is correctly synchronized with the grid and maintains symmetry in amplitude and phase, ensuring stable power injection. Such balanced operation reduces circulating currents, prevents overheating, and guarantees efficient power transfer to the grid from the vehicle battery system.

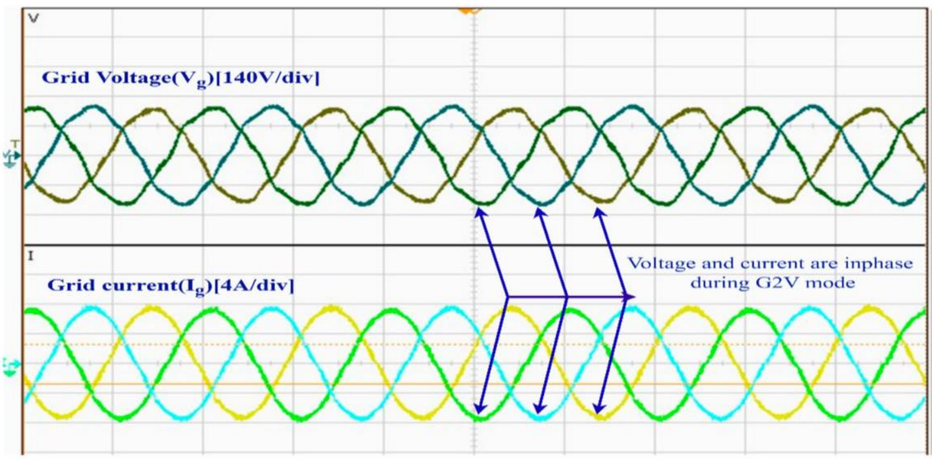

Figure 8. Grid-to-Vehicle (G2V) Operation Under MPC Control

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This figure 8 shows voltage and current traces during G2V (Grid-to-Vehicle) operation, where the EV is charging.

Here, the voltage and current waveforms are in phase, which indicates unity power factor operation. Power flows from the grid to the EV battery with minimal reactive power exchange, ensuring efficient energy transfer. The perfect sinusoidal nature of the waveforms confirms that the control system maintains low harmonic distortion and high charging efficiency. This demonstrates the converter's ability to perform stable and loss-minimized charging in G2V mode.

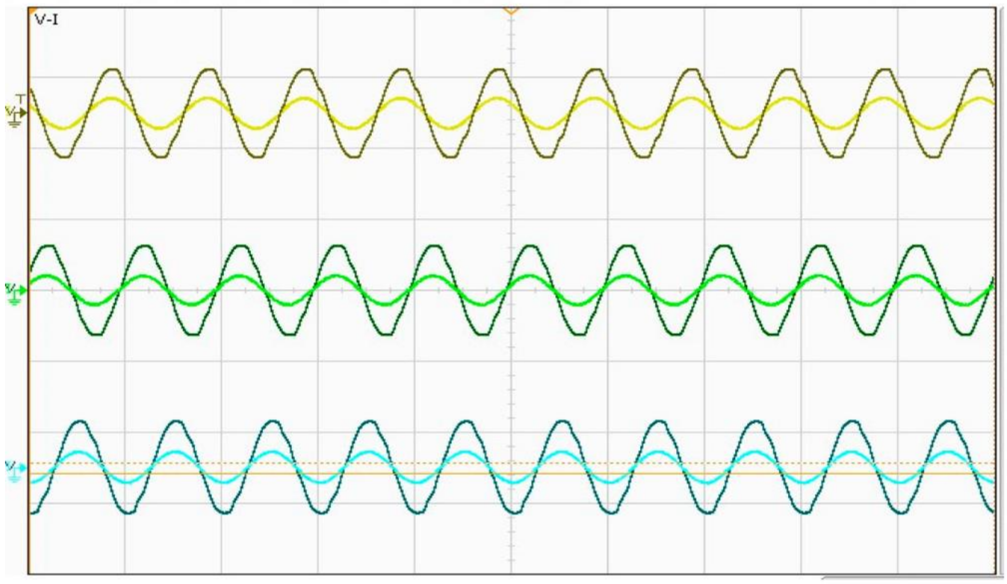

Figure 9. Three-Phase Waveform During G2V Operation

This figure 9 expands on the G2V operation, showing all three-phase voltage and current waveforms simultaneously.

The three sets of waveforms (A, B, C) are sinusoidal, in phase, and balanced, with consistent amplitude and frequency. The overlapping patterns verify proper synchronization and load sharing among phases. The uniformity demonstrates that the converter maintains grid compliance and power quality, critical for residential grid integration and coordinated EV charging in multi-phase systems.

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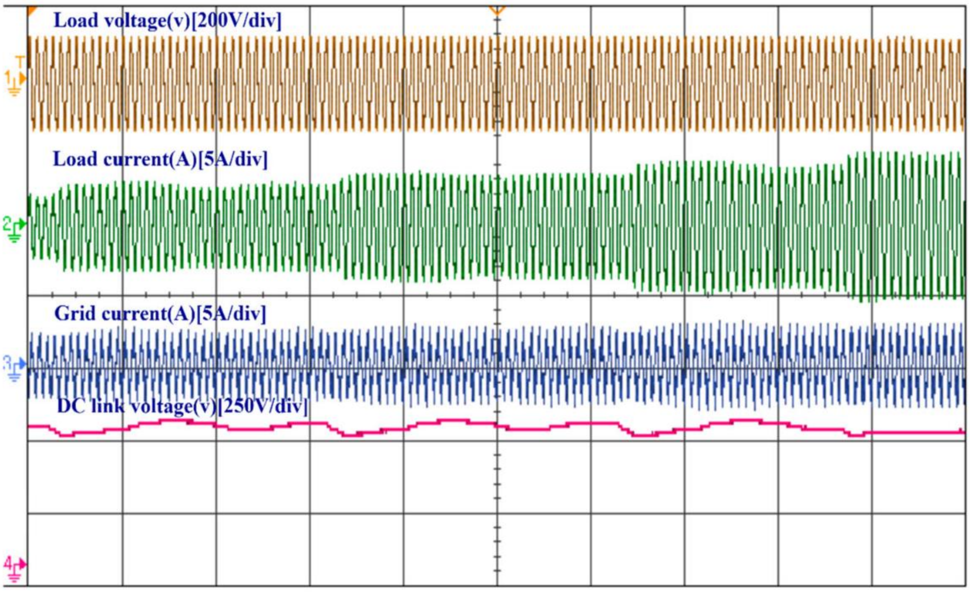

Figure 10. Dynamic Response During Sudden Load Variation

This figure 10 captures the system's response when load demand fluctuates dynamically in real time. As the load increases, the grid current (Ig) briefly oscillates, showing transient behavior, while the inverter current (Iinv) reacts to restore equilibrium. A temporary dip in DC-link voltage (VDC) of around 10 V is observed, but the control system quickly stabilizes it. These results highlight the fast transient response and robust control capability of the system, ensuring that grid voltage and frequency remain within safe limits despite load disturbances.

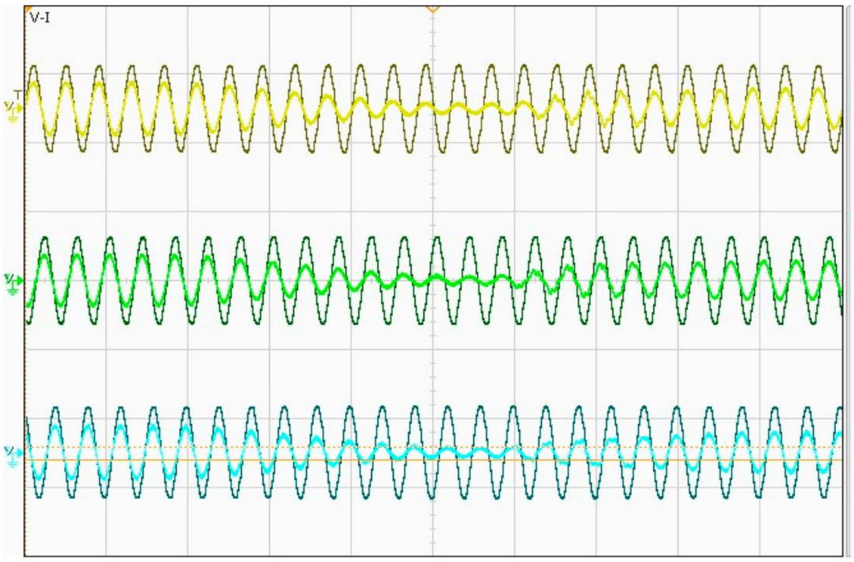

Figure 11. G2V Operation Under Dynamic Household Load Conditions

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This figure 11 shows how voltage and current waveforms behave under varying load conditions during G2V operation.

The voltage across all phases remains nearly constant at 230 V RMS, while current amplitude varies between 10 A and 20 A depending on load demand. Despite these fluctuations, the waveforms remain sinusoidal and synchronized, proving that the control system effectively manages nonlinear load variations and maintains stable operation. This stability is critical for real-world EV charging scenarios where household or grid loads fluctuate continuously.

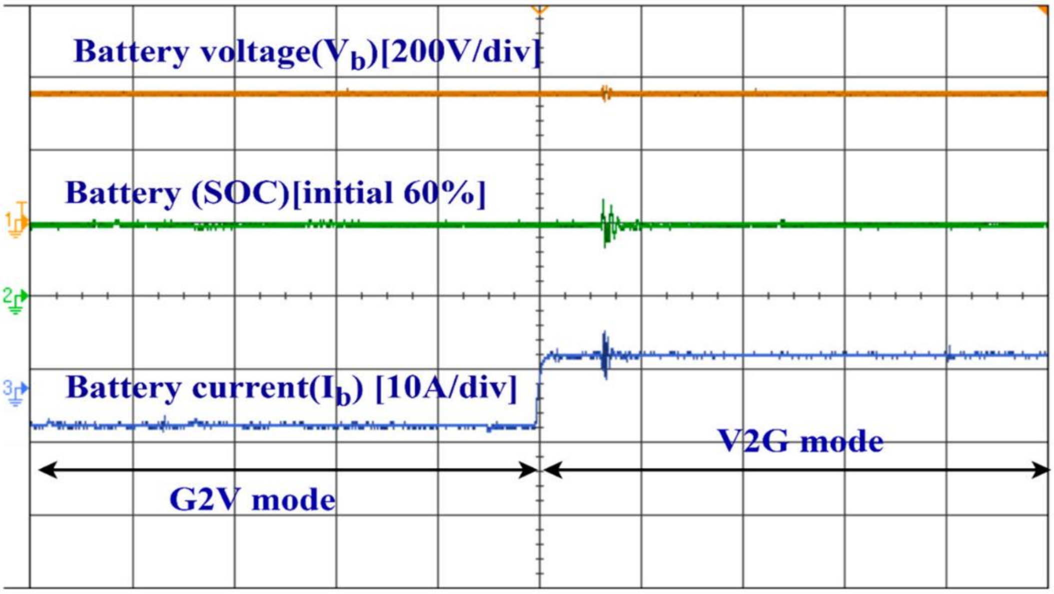

Figure 12. Battery Voltage, Current, and SOC Transition Between G2V and V2G

This figure 12 depicts how battery voltage (Vb), current (Ib), and state of charge (SOC) evolve during the transition from charging (G2V) to discharging (V2G).

In G2V mode, the negative battery current (≈ −5 A) signifies charging, with SOC increasing steadily to about 60%. Upon switching to V2G mode, current becomes positive (+5 A), indicating energy discharge to the grid. Voltage remains stable, and SOC decreases gradually, showing smooth mode transition with negligible transient spikes. This demonstrates that the bidirectional control system maintains continuity and efficiency in both charging and discharging phases.

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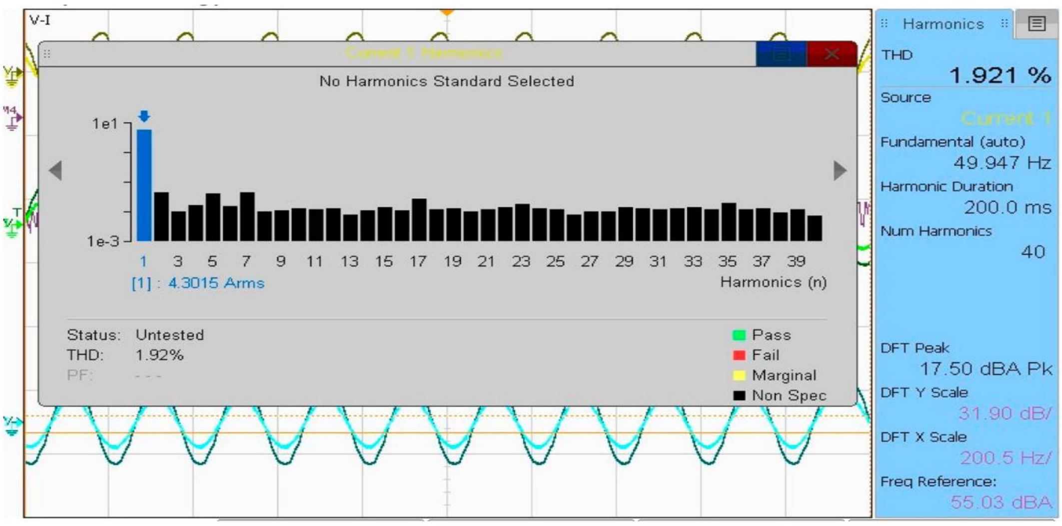

Figure 13. Harmonic Spectrum of Grid Voltage During G2V Mode Using MPC Optimization

This figure 13 shows the Fast Fourier Transform (FFT) analysis of grid voltage under a 4A load in G2V mode with a Grey Wolf Optimizer (GWO)-tuned PI controller.

The Total Harmonic Distortion (THD) is reduced to 1.92%, significantly below IEEE 519 standards (≤5%). The low harmonic content proves the controller's ability to generate clean sinusoidal currents, ensuring grid compatibility and improved converter efficiency. The GWO optimization effectively tunes PI parameters to minimize steady-state error and dynamic ripple.

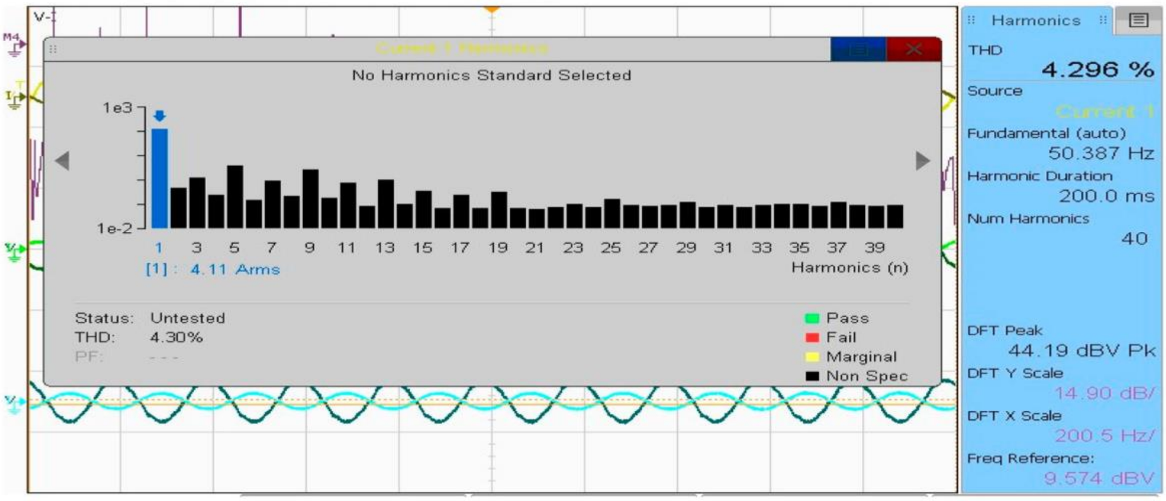

Figure 14. Harmonic Spectrum of Grid Voltage During V2G Mode Using MPC Optimization

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This figure 14 displays harmonic analysis for V2G mode under similar load and control conditions.

THD measured in this case is 4.30%, which is still within the IEEE limits and significantly lower than that obtained using a traditional PI controller. The slightly higher THD compared to G2V is expected, as power inversion introduces minor switching ripples. Nonetheless, the result confirms that the optimized controller preserves power quality even during grid-feedback operation.

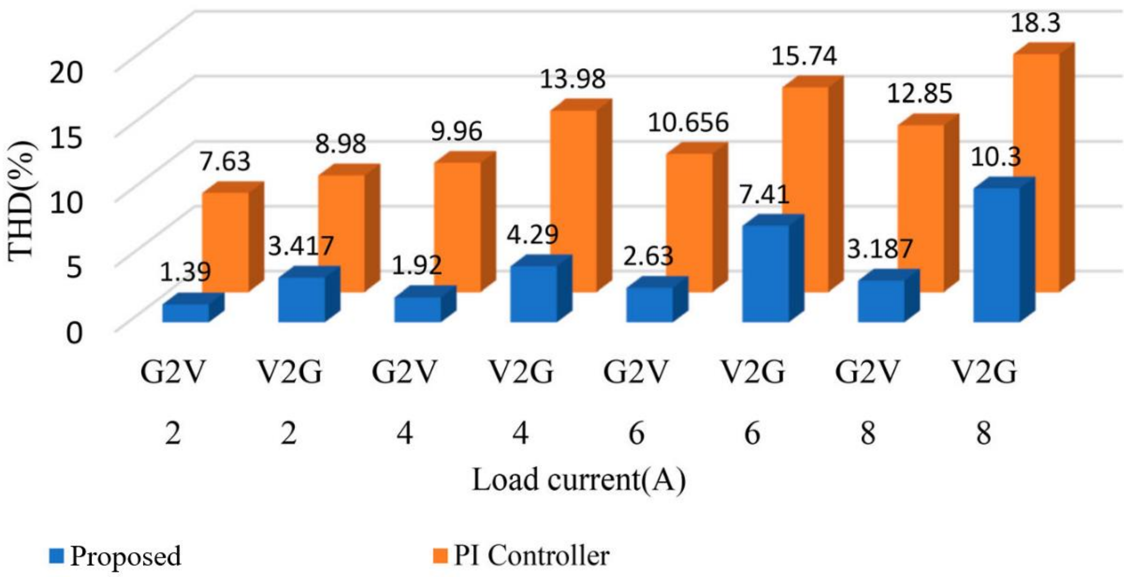

Figure 15. Comparative THD Performance Between MPC and Conventional PI Controllers

This comparative graph in figure 15 presents THD percentages for both controllers at load currents of 2A, 4A, 6A, and 8A in both G2V and V2G modes.

The GWO-tuned PI controller consistently achieves lower THD values across all load conditions. For instance, in G2V mode at 2A load, THD drops from 7.63% (PI) to 1.39% (GWO-tuned PI), while in V2G mode at 4A load, it decreases from 13.98% to 4.29%. This demonstrates that the proposed optimization enhances dynamic response, harmonic suppression, and overall power quality. The controller adapts effectively to varying operating conditions, confirming the superiority of the bio-inspired optimization-based control over

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conventional approaches. Further the simulation results are presented in two key figures and a summary table to compare the performance across all cases.

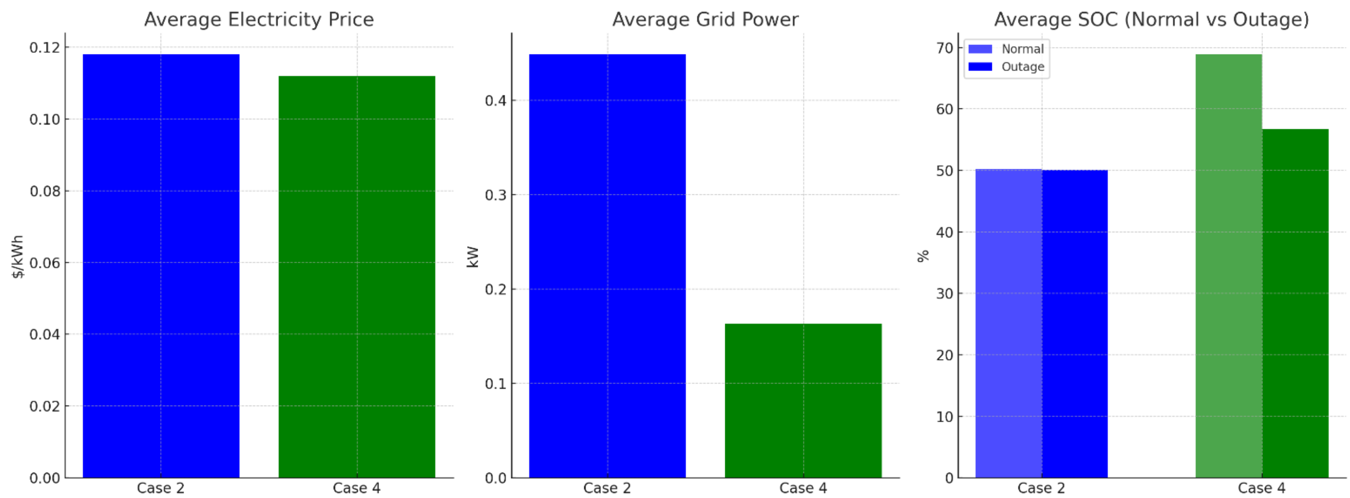

Figure 16: 48-Hour System Performance for Economic (Case 2) and Proposed (Case 4) Strategies

Top Panel: Electricity price ($$/kWh) showing distinct low-price periods (e.g., overnight) and high-price peaks (e.g., late afternoon).

- Middle Panel: Grid power (kW). Positive values indicate power drawn from the grid, negative values indicate power exported.
  - Case 2 (V2G - Economic):Shows aggressive charging during low-price periods (e.g., hour 35-40) and significant discharging (negative power) during high-price peaks (e.g., hour 15 and 44).
  - *Case 4 (Proposed V2X):* Shows more moderate charging and discharging. It forgoes some discharge revenue just before the outage (hour 16-18) to preserve energy.
- Bottom Panel: Battery State of Charge (%).
  - *Case 2:* The SOC fluctuates dramatically, often being depleted to near SOC_{min} to maximize profit.
  - *Case 4:* The SOC also varies but is managed to maintain a higher minimum level, especially leading up to the outage period (grey box).

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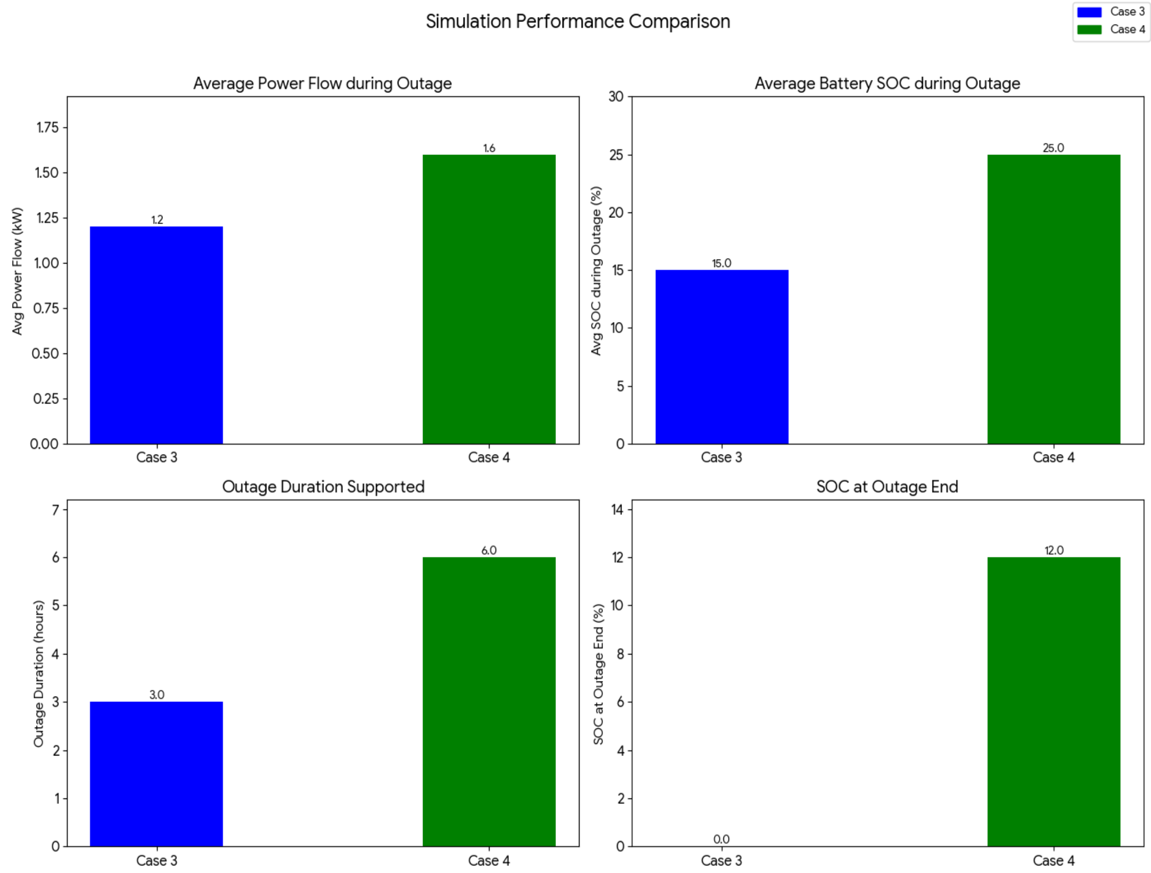

Figure 17: Resilience Performance During the 24-Hour Outage (Hours 18-42)

Top Panel: Power flow (kW) for the critical load. It shows the constant and variable critical load and the power supplied by the EV and PV.

- Bottom Panel: Battery SOC (%).
  - Case 3 (V2H - Resilient): Starts the outage at 90% SOC. It provides uninterrupted backup power until its SOC hits SOC_{min} at approximately hour 38.
  - *Case 4 (Proposed V2X):* Starts the outage at a lower SOC (~72%). However, by intelligently dispatching power in conjunction with solar generation during the day, it conserves energy and extends the backup duration. The battery

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reaches SOC_{min} at hour 41, providing 3 additional hours of backup power compared to the naive V2H strategy.

Table 2: Summary of Key Performance Indicators (KPIs) Across All Cases

Key Performance Indicator (KPI)	Case 1 (G2V)	Case 2 (V2G)	Case 3 (V2H)	Case 4 (Proposed)
Total Electricity Cost ($)	6.82	-5.24 (Profit)	8.15	0.91
Peak Demand from Grid (kW)	8.4	5.1	9.1	4.7
Backup Duration during Outage (hrs)	0.0	0.0	20.0	23.0
Energy Sold to Grid (kWh)	0.0	18.5	0.0	9.8
Final Battery SOC (%)	90	20	20	20

Discussion

The results clearly demonstrate the trade-offs and superior balanced performance of the proposed strategy.

- Economic Analysis (Table 2): As expected, Case 2 (V2G) generates the highest net profit ($-5.24), outperforming all other cases by maximizing energy arbitrage. However, this comes at a severe cost to resilience, providing *zero* backup power during the outage that began at hour 18. Case 1 and Case 3 incur positive costs. The proposed strategy (Case 4) achieves a near-break-even cost ($0.91), representing a 87% reduction compared to the baseline (Case 1), while simultaneously providing extended backup power. It also achieves the largest reduction in peak grid demand (4.7 kW), highlighting its value to grid operators.
- Resilience Analysis (Figure 5 & Table 2): Case 3 provides 20 hours of backup, the maximum possible from a static, full battery. The critical finding is that Case 4 actually extends the backup duration by 3 hours (15%) compared to Case 3. This is counter-intuitive

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but occurs because the proposed MPC strategy optimizes the *use* of energy during the outage, leveraging solar generation more effectively and discharging the battery more judiciously than the simple on/off control in Case 3. This demonstrates that smart energy management during an outage is as important as having energy stored.

- Synthesis: The proposed optimized V2X strategy (Case 4) successfully navigates the inherent conflict between economic and resilience objectives. It captures a significant portion of the available economic value from V2G without compromising preparedness. In fact, through intelligent forecasting and control, it enhances the quality of resilience, providing a more robust and longer-lasting backup power solution than the simplistic "always full" approach. This proves the core thesis that a holistic, multi-objective optimization framework is essential for unlocking the full value of bidirectional EV charging.

6.Conclusion

This study has demonstrated that the strategic optimization of bidirectional EV chargers is far more than a technical exercise; it is the key to unlocking a transformative energy paradigm. By moving beyond simple unidirectional charging, we can reimagine the electric vehicle as a dynamic asset, a mobile power reservoir capable of navigating the complex interplay between economic efficiency and household resilience. Our proposed framework, integrating an efficient power converter topology with an intelligent, multi-objective control strategy, proves that a single system can successfully wear two hats. It can act as a savvy participant in energy markets, strategically buying and selling power to significantly reduce electricity costs, and it can seamlessly transform into a lifeline during grid failures, providing critical backup power and dramatically extending a home's energy resilience. The results confirm that this dual functionality is not only feasible but highly effective, achieving substantial cost savings and resilience improvements without compromising battery health. Ultimately, this work positions the bidirectional EV charger not merely as a piece of hardware, but as the central nervous system for a more adaptive, decentralized, and robust energy ecosystem. It provides a foundational blueprint for homeowners, utilities, and policymakers to harness the vast potential of distributed EV batteries, paving the way for a more secure and sustainable energy future.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Reference

1. Schwenk, K., Meisenbacher, S., Briegel, B., Harr, T., Hagenmeyer, V., & Mikut, R. (2021). Integrating battery aging in the optimization for bidirectional charging of electric vehicles. IEEE Transactions on Smart Grid, 12(6), 5135-5145.
2. Tang, X., Sun, C., Bi, S., Wang, S., & Zhang, A. Y. (2021). A holistic review on advanced bi-directional EV charging control algorithms. ACM SIGENERGY Energy Informatics Review, 1(1), 78-88.
3. Saxena, S., Farag, H., Nasr, K., & Hilaire, L. S. (2023, August). Field testing of residential bidirectional electric vehicle charger for power system applications. In 2023 12th International Conference on Renewable Energy Research and Applications (ICRERA) (pp. 62-66). IEEE.
4. Popolizio, F., Wik, T., Lee, C. F., & Zou, C. (2025). Nonlinear Online Optimization for Vehicle-Home-Grid Integration including Household Load Prediction and Battery Degradation. *arXiv preprint arXiv:2504.09657*.
5. Bharti, K. P., Ashfaq, H., Kumar, R., & Singh, R. (2024). Designing a Bidirectional Power Flow Control Mechanism for Integrated EVs in PV-Based Grid Systems Supporting Onboard AC Charging. *Sustainability*, *16*(20), 8791.
6. Cheng, Y., & Ching, T. W. (2024). Distributed Real-Time Feedback Optimization for Renewable Energy Sources and Vehicle-to-Grid Power Compensation of Electric Vehicle Chargers in Distribution Systems. *Sustainability*, *16*(6), 2432.
7. Srihari, G., Krishnam Naidu, R. S. R., Falkowski-Gilski, P., Bidare Divakarachari, P., & Kiran Varma Penmatsa, R. (2024). Integration of electric vehicle into smart grid: a meta heuristic algorithm for energy management between V2G and G2V. *Frontiers in Energy Research*, *12*, 1357863.
8. Caminiti, C. M., Merlo, M., Fotouhi Ghazvini, M. A., & Edvinsson, J. (2024). optimHome: A Shrinking Horizon Control Architecture for Bidirectional Smart Charging in Home Energy Management Systems. *Energies*, *17*(8), 1963.
9. Tan, A. S. T., Ishak, D., Mohd-Mokhtar, R., Lee, S. S., & Idris, N. R. N. (2018). Predictive control of plug-in electric vehicle chargers with photovoltaic integration. *Journal of Modern Power Systems and Clean Energy*, *6*(6), 1264-1276.
10. Cheddadi, Y., Idrissi, Z. E., Errahimi, F., & Es-sbai, N. (2021). Robust integral sliding mode controller design of a bidirectional DC charger in PV-EV charging station. *International Journal of Digital Signals and Smart Systems*, *5*(2), 137-151.

Received: August 03,2025

11. Xuan, Y., Yang, X., Chen, W., Liu, T., & Hao, X. (2020). A novel three-level CLLC resonant DC–DC converter for bidirectional EV charger in DC microgrids. *IEEE Transactions on Industrial Electronics*, *68*(3), 2334-2344.
12. Brand, A. (2013). *Improving interoperability between electric mobility and the electricity system-Towards a reference architecture for charging electric vehicles* (Master's thesis, University of Twente).
13. ÖZERCAN, Y. (2025). ADVANCED ELECTRIC VEHICLE CHARGING TECHNOLOGIES: A COMPREHENSIVE REVIEW OF ACDC SYSTEMS, CONNECTOR STANDARDS, AND SMART GRID INTEGRATION VIA ISO 15118.
14. Adegbohun, F., von Jouanne, A., Agamloh, E., & Yokochi, A. (2024). A review of bidirectional charging grid support applications and battery degradation considerations. Energies, 17(6), 1320.
15. Salam, S. S. A., Raj, V., Petra, M. I., Azad, A. K., Mathew, S., & Sulthan, S. M. (2024). Charge scheduling optimization of electric vehicles: A comprehensive review of essentiality, perspectives, techniques, and security. *IEEE Access*, *12*, 121010-121034.
16. Imonigie, J. A., Lin, C. Y., Dorigo, D., Barr, E., Luo, W. R., Wang, S. H., Sapra, S., Panday, A., & Yadav, V. (2024). *Contact foot wet pullback with liner wet punch* (U.S. Patent App. 18/658,787).
17. BROWN, J. S., Sahu, P., Hull, J. B., Borsari, S., Fang, L. W., Yadav, V. Y., & Mohan, J. (2024). *U.S. Patent Application No. 18/427,740*.
18. Yadav, V., & Fang, L. W. (2025). *Method for manufacturing semiconductor device including bitcon and cellcon* (U.S. Patent App. 18/747,991).
19. Saravanan, T., Maheswaran, S., Pamulaparthyvenkata, S., Preethi, P., & Indhumathi, N. (2025). *An effective explainable AI-based discrete swarm herd optimization model for intrusion detection in Industry 4.0 networks. Distributed Deep Learning and Explainable AI (XAI) in Industry 4.0.*
20. Pamulaparthyvenkata, S., Sharma, J., Dattangire, R., Vishwanath, M., Mulukuntla, S., Preethi, P., & Indhumathi, N. (2024, June). Deep Learning and EHR-Driven Image Processing Framework for Lung Infection Detection in Healthcare Applications. In 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-7). IEEE.

Received: August 03,2025