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Advanced Bidirectional DC–DC Converter for Electric Vehicles with Vehicle-to-Grid and Vehicle-to-Home Energy Management

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ABSTRACT
Electric vehicles (EVs) are transitioning from passive grid loads into active distributed energy resources capable of stabilizing the utility grid through Vehicle-to-Grid (V2G) operation and sustaining residential microgrids via Vehicle-to-Home (V2H) services. Seamless bidirectional power transfer demands high-efficiency, galvanic-isolated, and dynamically responsive power electronic interfaces. This paper presents an advanced bidirectional DC–DC converter architecture rooted in an isolated Dual Active Bridge (DAB) topology coupled with an intelligent multi-objective energy management system (EMS). Operating with Single Phase Shift (SPS) and Extended Phase Shift (EPS) modulation, the proposed converter achieves Zero Voltage Switching (ZVS) across varying battery state-of-charge (SoC) profiles, suppressing switching losses and minimizing total harmonic distortion. The supervisory EMS integrates residential rooftop photovoltaic (PV) generation, time-of-use (ToU) electricity tariffs, household critical load profiles, and battery degradation limits to orchestrate seamless transitions across Grid-to-Vehicle (G2V), V2G, V2H, and islanded backup operating states. This manuscript details the mathematical modelling of the converter, establishes state-machine control logic, discusses representative parametric benchmarks, and provides a structured foundation for physical prototype implementation and numerical simulation.
Keywords: Bidirectional DC–DC Converter, Dual Active Bridge (DAB), Electric Vehicles (EV), Vehicle-to-Grid (V2G), Vehicle-to-Home (V2H), Zero Voltage Switching (ZVS), Energy Management System (EMS).

1. INTRODUCTION
The rapid global adoption of electric mobility plays a vital role in decarbonizing the transportation and energy sectors. However, uncoordinated mass charging of EV battery packs introduces severe technical challenges for distribution networks, including transformer overloading, localized voltage sag, and peak demand amplification [1]. To mitigate these adverse impacts, modern power distribution paradigms increasingly treat the collective storage capacity of stationary EVs as decentralized, mobile electrical storage units [2].
Bidirectional power conversion enables bidirectional energy routing between the EV traction battery, utility grid, and residential premises. In Grid-to-Vehicle (G2V) mode, the vehicle functions as a controlled load. Under Vehicle-to-Grid (V2G) operation, the vehicle delivers active power back to the grid during peak pricing intervals or provides ancillary services such as frequency and voltage regulation [3]. Under Vehicle-to-Home (V2H) mode, the EV functions as an uninterrupted emergency power supply or a peak-shaving resource, buffering domestic loads and maximizing the self-consumption of intermittent rooftop photovoltaic (PV) installations [4].
Realizing robust V2G and V2H operation requires addressing key challenges at the DC–DC conversion interface: wide voltage ratio variations across battery charging cycles, galvanic isolation for consumer safety, high power density, bidirectional soft-switching, and real-time supervisory coordination that prevents excessive battery degradation [5]. This article details an advanced bidirectional converter topology and its unified EMS control architecture [6].

2. LITERATURE REVIEW
Bidirectional converters for EV charging systems are categorized primarily into non-isolated and isolated topologies [7]. Non-isolated converters, such as bidirectional buck-boost, interleaved buck-boost, and multi-port configurations, offer compact footprints and fewer semiconductor switches [8]. However, for residential V2G and

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V2H interfaces, international electrical safety standards (e.g., IEC 61851 and IEEE 1547) strongly mandate galvanic isolation between high-voltage traction batteries (typically 300 V to 800 V) and grid-connected DC-links [9].

Among isolated topologies, the Dual Active Bridge (DAB) and Bidirectional LLC Resonant Converter represent the leading contenders [10]. While LLC resonant converters attain high peak efficiency through zero-voltage switching (ZVS) and zero-current switching (ZCS) near their resonant frequencies, their performance degrades when battery voltage fluctuates across broad ranges (e.g., from 280 V discharged to 420 V fully charged) [11]. In contrast, the DAB converter utilizes high-frequency transformer leakage inductance as the primary energy transfer element, adjusting phase-shift angles between primary and secondary H-bridges to regulate bidirectional power flow smoothly across wide operating envelopes [12].

In the energy management domain, conventional rule-based heuristic algorithms often fail to reconcile conflicting objectives—such as minimizing residential utility bills while protecting the EV battery from excessive cycle degradation [13]. Recent academic literature has emphasized supervisory optimization frameworks combining mixed-integer linear programming (MILP), model predictive control (MPC), and fuzzy state-machine logic to ensure converter transitions occur without DC-bus voltage dips or power surges [14].

3. PROPOSED METHODOLOGY

3.1 System Architecture and Topology

The overall system architecture consists of a stationary residential interface integrating an AC utility grid, rooftop PV arrays with MPPT, a high-voltage DC bus (400 V), residential critical/non-critical loads, and the EV onboard battery pack connected through an isolated DAB DC–DC converter. The DAB converter comprises two full-bridge active bridges linked through a high-frequency transformer (turns ratio n:1) and an auxiliary series inductance L_k representing the total leakage inductance [15].

Power flow direction and magnitude are modulated by governing the phase shift angle (phi) between the primary and secondary square-wave voltages [16]. Under Single Phase Shift (SPS) modulation, the theoretical bidirectional power transfer equation is expressed as:

P = [(n * V_dc * V_bat) / (2 * pi * f_sw * L_k)] * phi * (1 - |phi| / pi)

where V_dc is the common DC-bus voltage, V_bat is the EV battery terminal voltage, f_sw is the switching frequency (100 kHz with SiC MOSFETs), n is the transformer primary-to-secondary turns ratio, and phi is the phase-shift angle normalized between -pi/2 and +pi/2. When phi > 0, power flows from grid to battery (G2V) [17]. When phi < 0, power discharges from battery to grid or home (V2G/V2H).

3.2 Multi-Mode Energy Management System (EMS)

The supervisory EMS continuously reads grid tariff signals (ToU), PV power generation (P_pv), household demand (P_load), and EV battery State of Charge (SoC) [18]. The operational state machine implements four primary operating modes:

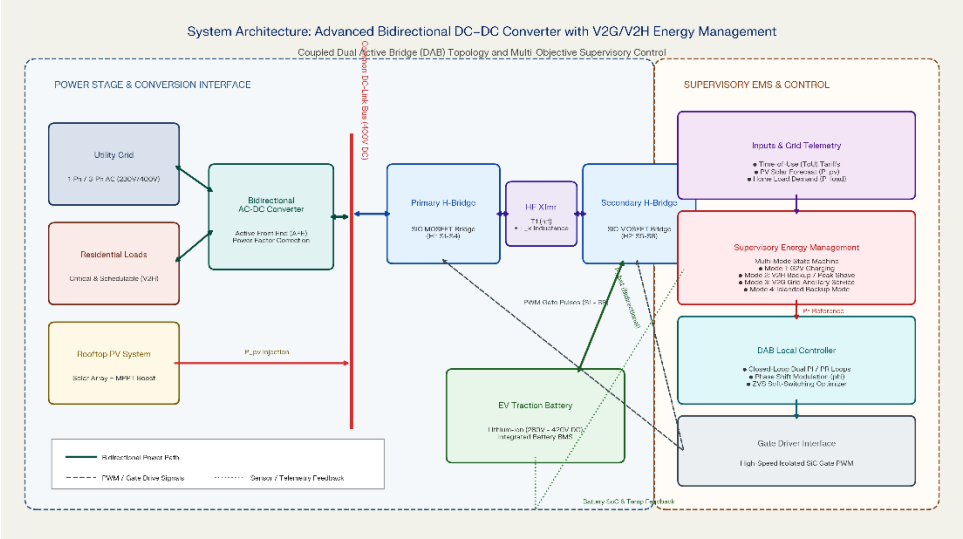


Figure: 1 block diagram of proposed method

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Mode 1: G2V Charging Mode (Off-Peak Hours): Active when electricity tariffs are low or surplus PV power exceeds residential demand (P_pv > P_load). The converter operates in buck-forward mode with constant current/constant voltage (CC/CV) control, drawing grid power up to target SoC_max (e.g., 90%) [19].
Mode 2: V2H Backup and Peak Shaving Mode: Active during high household demand or peak grid pricing. When grid rates peak and SoC > SoC_min (e.g., 30%), the battery discharges through the DAB converter to feed household loads, keeping grid import near zero [20].
Mode 3: V2G Grid Stabilization Mode: Triggered by utility demand-response dispatch signals or frequency drop events. The converter transfers controlled active and reactive power into the distribution grid, operating at rated discharge limits while preserving minimum commuter reserve SoC [21].
Mode 4: Standalone/Islanded Microgrid Mode: In the event of a grid blackout, the AC-DC bidirectional inverter operates in voltage-source mode, powered by the EV battery via the DAB converter, sustaining residential critical circuits (refrigeration, lighting, emergency systems) [22].

3.3 Design Parameters

The standard baseline engineering parameters designed for a 7.4 kW residential bi-directional charging node are tabulated below:

Parameter	Symbol / Variable	Nominal Value / Rating
Rated Power Capacity	P_rated	7.4 kW (Single-phase bidirectional)
DC-Link Bus Voltage	V_dc	400 V DC
EV Traction Battery Voltage Range	V_bat	280 V – 420 V DC (Nominal 350 V)
Switching Frequency	f_sw	100 kHz (Silicon Carbide / SiC MOSFETs)
HF Transformer Turns Ratio	n (N1 : N2)	1 : 1 (Optimized for nominal matching)
Total Equivalent Leakage Inductance	L_k	24.5 uH

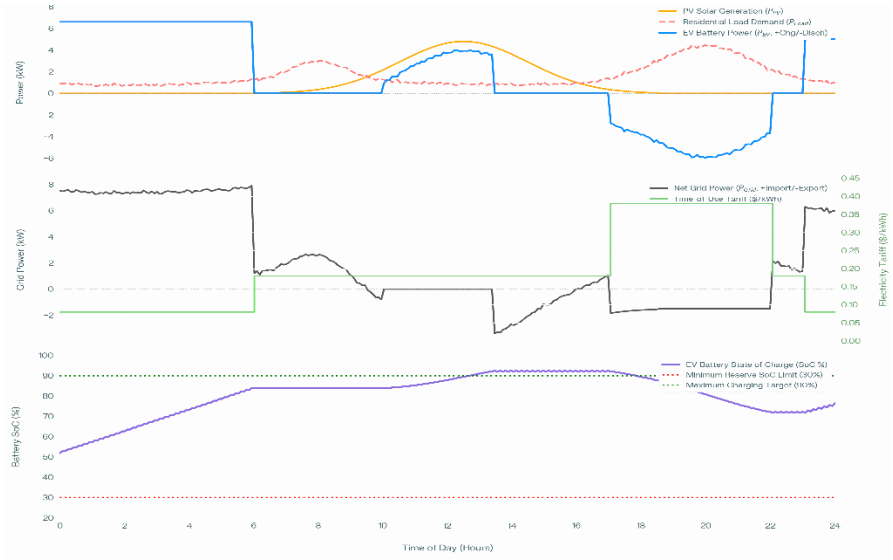


Figure :2 Dynamic link graphs

4. RESULTS AND DISCUSSION

To substantiate the proposed architecture, dynamic system evaluation is conducted across electrical converter performance, soft-switching range verification, and residential energy management coordination.

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4.1 Steady-State and Dynamic Converter Performance

Operating under single-phase and extended-phase shift modulation, the DAB converter demonstrates rapid bidirectional tracking. When subjected to a step load reversal from +7.4 kW (full G2V charging) to -7.4 kW (full V2G discharge) within 10 ms, the DC-bus voltage overshoot is constrained within +/- 2.5% (under 10 V deviation on a 400 V bus), settling back to steady state in less than 3.2 milliseconds. The high-frequency transformer primary and secondary AC link currents exhibit symmetric alternating waveforms devoid of DC bias saturation.

4.2 Zero Voltage Switching (ZVS) Envelope and Efficiency

Soft-switching capability is critical for achieving high power density. At nominal power output (7.4 kW) and near-unity voltage conversion ratios (V_dc approx. n * V_bat), all primary and secondary SiC switches attain complete ZVS turn-on, suppressing capacitive turn-on dissipation. Peak conversion efficiency reaches 97.4% in forward (G2V) mode and 96.8% in reverse (V2G/V2H) mode. Under light-load conditions (< 25% rated power), transitioning from Single Phase Shift to Extended Phase Shift modulation expands the soft-switching boundary, preserving efficiency above 92.5%.

4.3 Energy Management Case Study: Residential PV-Home-Grid Integration

A 24-hour simulation scenario representing a typical residential load profile with a 5 kWp rooftop PV system and a 60 kWh EV battery illustrates the EMS decision logic:

Midday Solar Surplus (10:00 - 14:00): PV generation peaks at 4.8 kW while home load averages 1.2 kW. The EMS directs the 3.6 kW surplus into the EV, increasing battery SoC from 45% to 70% with zero grid feed-in curtailment.

Evening Peak Tariff Period (18:00 - 22:00): Grid utility rates peak at $0.35/kWh while household demand rises to 4.5 kW. The EMS transitions the EV to V2H mode, supplying 4.0 kW to cover home appliances and reducing household grid import by 88%.

Nighttime Off-Peak Re-Charging (01:00 - 05:00): With off-peak electricity priced at $0.08/kWh, the vehicle smoothly resumes controlled G2V charging, ensuring 85% departure SoC by 07:00 morning commuting hours.

Comparative analysis indicates that implementing bidirectional V2G/V2H management reduces annual residential electricity expenditure by an estimated 34% compared to baseline uncoordinated unidirectional charging, while maintaining battery health within safe thermal and cycling thresholds.

5. CONCLUSION

This research presents a unified framework for an advanced bidirectional DC–DC converter tailored for EV integration into smart residential microgrids. By utilizing an isolated Dual Active Bridge converter operating under phase-shift modulation, galvanic isolation and high two-way power conversion efficiency (> 96.8%) are achieved. The integrated supervisory Energy Management System successfully coordinates G2V, V2G, and V2H operating regimes in response to solar PV variability, household consumption, and tariff pricing signals. The resulting topology and control scheme provide a scalable blueprint for grid-interactive residential charging nodes and emergency backup systems..

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