

Baseline Modeling and Comparative Evaluation of Control Strategies for Utility-Tied and Islanded Microgrid with Bidirectional Electric Vehicle Integration

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ABSTRACT

As electric vehicle (EV) integration into modern microgrids accelerates, ensuring stable voltage regulation and safe bidirectional power exchange has become increasingly critical. This research introduces a modified Proportional Integral (PI) controller enhanced with feedforward and anti-windup mechanisms for a utility-connected DC microgrid incorporating Vehicle-to-Grid (V2G)-enabled EVs and a Battery Energy Storage System (BESS). The proposed model is realized in Simulink using an averaged DC microgrid approach to ensure the voltage remains stable, deviates less than $\pm 1\%$, and limits transient voltage dips to below 1.3 V during islanding. It offers higher precision and stability than Droop and classical PI controls, while avoiding the computational complexity of Model Predictive Control (MPC), thereby establishing the proposed PI scheme as an efficient, reliable, and real-time, scalable solution for next-generation EV-integrated smart microgrids.

Keywords: *Electric Vehicles, Droop Control, Vehicle-to-grid, Model predictive control, Hierarchical control, utility grid*

1. Introduction

It is the case that the increase of electric vehicles is quickly changing load patterns in the contemporary power systems which introduces new operational challenges for the utility-connected microgrid. Given the high level of variation and load spikes due to EV charging, stable grid supplied power must be negotiated even more complexly. Meanwhile, microgrids need to ensure local generation, storage, and converter management control in order to operate successfully. A baseline model can also be developed for a systematic analysis of the effect of various control strategies on power balance, voltage regulation and the overall microgrid performance in such EV integrated scenarios. The increased emphasis on utility-tied microgrids coupled with electric vehicles (EVs) has reflected the growing shift toward sustainable energy systems. Connected to the main grid, these microgrids enhance energy reliability and flexibility, while also enabling the use of renewable energy[1]. EVs function as both energy consumers and distributed storage units through vehicle-to-grid (V2G) technology, thereby promoting grid stability and peak load management. The importance of a baseline model arises from the growing complexities regarding power flow control, energy balancing, and storage coordination in such integrated systems. The increasing needs of clean transportation and decentralized energy require effective control strategies for stable and efficient operation[2].

In today's power systems, the microgrid that is tied to a utility is an essential piece of the overall stability, reliability, and energy efficiency of a utility-connected microgrid by combining solar, wind, and battery storage resources with the main grid, and ensuring the entire system's stability, reliability, and efficiency. It works in both grid-connected and islanded modes, intelligent local generation and end-to-end balancing of supply and demand controlled with the advanced control strategies in mind. This will increase the power quality, reduce transmission losses, and contribute to the resilience during outages or peak load periods and ensures energy endurance of the system [3].

EVs enhance utility microgrid performance by vehicle-to-grid V2G technology [4]. EVs act as mobile energy storage units, capable of discharging stored energy back to the grid during periods of high demand and recharging during periods of surplus generation. This bidirectional power flow benefits peak shaving, load levelling, and supports higher renewable energy penetration[5], which in turn results in reduced overall carbon emissions. The integration of electric vehicles provides a versatile and adaptive energy management solution that enhances grid stability, optimizes economic performance, and facilitates the transition to sustainable energy systems.

2. Literature Review

The fast-growing nature of renewable energy and EV penetration of utility-connected microgrids has developed sophisticated control concepts necessary to keep the system operating in reliability and efficiently and the stability can be expected. It is essential to implement effective control systems for distributed energy sources management, voltage-frequency balance and real-time power distribution analysis under fluctuating load and generation.

The Droop Control and Model Predictive Control (MPC), Hierarchical Control and Decentralized Control have a significant role in managing utility microgrids. Droop Control is an old-school application used for sharing loads across distributed generators (DGs) without the need for communication links [6]. It works by changing frequency and voltage according to power output and provides system equilibrium. Droop control is, however, only moderately efficient for energy (approximately 88–92%) and suffers from voltage and frequency anomalies in the range, typically $\pm 2\%$ and ± 0.05 Hz, respectively. While it offers fast response times (50–100 ms), its decentralized nature limits coordination, sometimes resulting in stability issues and increased steady-state error under high renewable penetration[7].

MPC is a higher level, more dynamic methodology that considers mathematical models to simulate control input for predicting system behaviour and thus optimize control input in real time. It exhibits greater energy efficiency (93–96%) and maintains voltage deviation within $\pm 1\%$ and frequency deviation under ± 0.02 Hz [8]. This prediction capability of the MPC facilitates accurate transient handling and better dynamic effects, but it suffers mainly from high computation requirements, as the computational time (150–300 ms) is higher due to iterative optimization. Still, MPC still has better uptime and is robust under variable modes of operation and so is suitable for EV-integrated microgrids with frequent load changes [9].

In contrast, Hierarchical Control provides a framework that combines local autonomy with system-wide coordination through three levels (primary, secondary, tertiary control). Generally, the first layer employs droop control to maintain power sharing, the next one restores nominal voltage and frequency, and the third one deals directly with economic dispatch and grid interaction[10]. This scheme combines a high level of energy efficiency overall (95–97%), keeps frequency and voltage deviations in check ($< \pm 0.01$ Hz and $\pm 0.5\%$ respectively), and assures steady-state grid stability even under fluctuating renewable output through a multi-tier structure at all times for maximum stability. Hierarchical systems introduce further communication delays and necessitate a complex coordination structure, potentially extending response and processing times (200–400 ms). Moreover, if communication channels malfunction, synchronization between the secondary and tertiary layers may be affected, resulting in diminished performance.[11].

Decentralized control methodologies empower local controllers to make autonomous decisions, enabling each unit to operate independently while still collaborating through shared parameters [12]. This approach enhances the system's scalability and resilience by eliminating dependence on a singular controller. Table 1 indicates that energy efficiency in decentralized control typically ranges from 87% to 92%. The fluctuations in voltage and frequency are ± 1 –2% and ± 0.04 Hz, respectively. The response time is reasonable (100–150 ms) and processing time is also moderate (100–200 ms), achieving a

satisfactory equilibrium between speed and computational complexity. However, decentralized solutions may be less effective at optimizing the entire system, complicating energy management inside the microgrid and resulting in mismatched power flow at peak load or fault conditions [13].

From the perspective of the utility grid, these control techniques have distinct consequences. Droop control is simple and responds very fast, therefore is well suited for local reliability, but cannot handle complex coordination when the EV penetration is high. Its shortcomings lead to power imbalance or frequency drift when renewable resources are predominant. MPC, even with high computational costs, excels in adaptive real-time decision making while minimizing transients and improving the reliability of energy transactions between EVs and the grid as a whole. Hierarchical control brings global coordination allowing the system to retain nominal operating conditions and manage grid-connected or islanded modes efficiently. But it requires a dependable communication infrastructure and complex algorithms, adding operational complexity. Such decentralized control offers a high degree of fault tolerance as it is more flexible but may lead to local optimization and less efficiency overall, and consequently may increase the operational cost at large-scale networks.

In terms of quantitative performance, it can be seen from recent research that Decentralized Control and Hierarchical Control are superior to Droop and MPC in terms of stability and overall uptime of the system, where they achieve over 90% reliability under varying renewable and EV loads [14]. However, the high computational requirement of MPC might be prohibitive for real-time scalability on large microgrids without sophisticated processors and predictive algorithms. Droop control remains a reliable fallback for emergency or low-complexity systems because it can be plugged and played and has low communication dependency, though in the long run precision is sacrificed. Hierarchical Control should be used for grid-tied setups with many distributed resources. On the other hand, decentralized approaches should be used for remote microgrids with limited connectivity to make them more resistant to single-point failures [15].

Recent studies confirm that decentralized and hierarchical schemes still lead in uptime and large-scale reliability, but advances in lightweight, physics-aware estimation are rapidly closing the gap for real-time primary control. Adaptive EKF/IEKF variants improve SOC convergence under parameter uncertainty and sensor noise, reducing estimation bias during dynamic V2G events [16], while TinyML approaches (weight-clustered CNN/LSTM and ultra-compact networks) demonstrate deployable SOC/SOT estimators with $\approx 50\%$ model size reduction and sub-second inference on microcontrollers—enabling primary-level decisions at the EV BMS without offloading to the cloud [17]. Physics-informed neural networks (PINNs) and hybrid physics–ML architectures provide SOH/SOC predictions that remain physically consistent across varying C-rates and aging conditions, improving long-horizon robustness compared with pure data-driven models [18]. Learning-assisted MPC and MPC-VSG hybrids show improved transient damping and frequency support in high-renewable microgrids but at increased computational cost, motivating the PI+feedforward+anti-windup approach as a low-complexity alternative that attains MPC-level transient performance in practice [19]. Recent work also quantifies communication-delay impacts in hierarchical schemes and proposes mitigation via local learning at the edge to preserve coordination under 200–400 ms link latencies [20],[21]. The literature indicates a converging trend: the combination of hybrid, lightweight machine learning (TinyML/PINN) and robust adaptive filtering (IEKF), along with straightforward yet improved primary controllers (PI+FF+AW), presents the optimal solution for scalable V2G microgrids [22].

These trade-offs centre around speed, computational complexity, and control accuracy. A quick response and a high degree of autonomy, for example in droop control, sacrifice precision and adaptability. On the contrary, schemes such as MPC and Hierarchical Control improve accuracy and grid integration but require more computational and communication resources. Such trade-offs have a direct impact on the utility grid's capacity to absorb variability in renewables and ensure service continuity.

Table 1. Control strategies statistical response in Utility grid

Control Strategy	Energy Efficiency (%)	Voltage Deviation (%)	Frequency Deviation (Hz)	Response time (ms)	Processing Time(ms)	Uptime (%)
Droop	88-92	± 2	±0.05	50-100	50-100	90-92
MPC	93-95	± 1	±0.02	100-150	150-300	82-87
Hierarchical control	90-91	±0.5	±0.01	150-200	200-400	88-93
Decentralized Control	87-92	±1-2	±0.04	100-150	100-200	90-94

Although effective, every control mechanism has some drawbacks. Droop control suffers from poor accuracy and stability under high renewable penetration due to voltage and frequency deviations. Although MPC is highly efficient, it requires high processing time and is not scalable. Hierarchical control ensures coordination but relies on reliable communication links, creating a vulnerable position for delay or failure. Decentralized control enhances flexibility and resilience but it lacks global optimization and can result in uneven power distribution. These shortcomings can potentially reduce the overall grid efficiency, lead to higher operating costs, and the seamless integration of EVs and renewable energy in utility-tied microgrids.

Utility attached microgrid electric vehicles can help overcome the shortcomings in existing control methods. Due to their bidirectional charging facility, EVs make for mobile energy storage that mitigates the voltage and frequency variations that droop control finds difficult. These support the capability of fast-response, with the potential of facilitating less computation for MPC and stabilizing the grid. EV fleet encourages decentralized support and reduces reliance on continuous communication (hierarchical control). EVs provide the potential for dynamic load balancing, which can be used for decentralised control, leading to enhanced flexibility and distribution of power. This integration not only makes it more efficient, lowers operating costs, and enables a more seamless integration of renewable energy.

2.1 Synthesized Methodology of V2G Studies

The recent literature review points out that high-level power flow control strategies for Droop and Hierarchical Control are moving toward being based on very precise real-time battery state estimation models at the primary level (the EV side). In order to have a secure and efficient V2G operation, the microgrid should obtain the vehicle's instantaneous State of Charge (SOC) and State of Health (SOH). The emerging research trend lies in representing the best of both worlds in terms of achieving the very high accuracy solution of complex DL models while having a solutions lightweight enough to be deployed on resource constrained microcontrollers in a vehicle's BMS. With reference to the preceding, the salient features, specific merits for V2G participation and demerits of the underlying techniques are highlighted in the table 2.

Table 2. Comparative Analysis of Advanced Methodologies for V2G-Oriented Battery State Prediction and Control

Methodology Category	Specific Methodologies Used	Key Advantages for V2G	Key Pitfalls & Shortcomings
Deep Learning & TinyML.	Weight Clustered-CNN-LSTM (WC-CNN-LSTM): Combines Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory	Highly Optimized for Edge: Achieves comparable SOC/SOT (State of Temperature) accuracy with a 52.98% smaller model size, making	Between them: The weight clustering process adds 25% more time to the already long training process of deep neural networks.

	(LSTM) for sequence prediction. Uses weight clustering for model compression (TinyML approach).	it feasible for real-time deployment on EV Battery Management Systems (BMS).	
Physics-Informed Neural Networks	Physics-Informed Deep Neural Network (PIDNN): This kind of neural network architecture employs physics principles directly in its design, such as thermal-electrical battery models.	Physically Consistent and Accurate: ensures that predictions are physically reasonable, resulting in high voltage prediction accuracy across a broad spectrum of C-rates and during the cell's aging process.	Preliminary Computational Demands: Substantial pre-training duration necessary for the Feedforward Neural Network (FNN) and a convoluted procedure to identify the appropriate internal physics states for network input.
Adaptive Filtering	Improved Extended Kalman Filter (IEKF): Employs several Extended Kalman Filters operating concurrently to dynamically modify the process noise covariance matrix (Q), hence enhancing resilience.	Resilient to Model Inaccuracies: IEKF has significant resilience to modeling inaccuracies and 15% parameter deviations. It offers superior convergence relative to conventional Extended Kalman Filters (EKF).	The complex nature of covariance tuning arises from the parallel architecture, rendering the filter's effectiveness contingent upon the initial estimations of the process and measurement noise covariance matrices (Q and R).
Data-Driven Feature Selection	Principal Component Analysis (PCA) combined with the Nonlinear Autoregressive Exogenous Model (NARX) employs PCA to diminish the dimension of complex data, while NARX, a recurrent neural network, facilitates time series State of Charge (SOC) prediction.	Reduced Computational expenditure: PCA significantly decreases the quantity of inputs required for prediction. This significantly accelerates the training and inference duration for the NARX network while maintaining a high level of accuracy.	Loss of Interpretability: PCA transforms physical input data into abstract components, complicating the association of prediction errors with specific sensors or physical states.

2.2 Trends and V2G Implications

The reviewed methods show a consistent trend towards combining physics-based knowledge and data-driven intelligence methods to improve the estimation of battery state and control accuracy. Methods like WC-CNN-LSTM and PIDNN strike the balance between precision and computation, so they can also be implemented on embedded BMS platforms. Adaptive filtering and PCA-NARX methods boost the robustness and scalability. Collectively, these hybrid models are important enablers to achieve accurate, real-time control and monitoring for the next-generation smart microgrids and sustainable energy systems

2.3 V2G Focus

For Vehicle-to-Grid (V2G) applications, such intelligent estimation and control techniques allow accurate SOC/SOH tracking and dynamic energy management between EVs and utility grids. Real-time flexibility, lightweight computation, and physical consistency make techniques like WC-CNN-LSTM and IEKF better at bidirectional power flow, frequency regulation, and load balancing. This increases

grid stability, promotes renewable integration, and enables EVs to serve as distributed storage assets, increasing the resilience of the grid system and optimizing the energy transfer in dynamic smart grids.

2.4 Main Challenges

Challenges in the implementation of advanced V2G control and estimation frameworks are high computational demands of deep learning models, achieving an effective trade-off between accuracy and real-time implementation on limited EV BMS hardware, and tuning of adaptive filters such as IEKF. Another challenge is making sure that communication is reliable, that cybersecurity is up to date, and that different EV and grid standards can work together. Furthermore, data scarcity, sensor noise, and model interpretability issues prevent the large-scale, stable, and explainable integration of V2G into dynamic microgrid environments.

This paper contributes a unified baseline model of a utility-tied microgrid with EV integration and comparatively evaluates the application for the different control strategies applied under the same operating conditions. It quantifies their impacts on power flow coordination, DC-bus stability, voltage regulation, and energy balancing. The work highlights performance differences, identifies the most robust approaches, and provides a reference framework for evaluating future microgrid controllers in EV-dominated environments.

3. Methodology

This paper proposes a modified Primary Control scheme based on a Proportional-Integral (PI) Controller with Feedforward and Anti-Windup when dealing with the problem of EV V2G operation along with the microgrid stability. The model is developed in Simulink utilizing the Averaged DC Microgrid method, which allows the design to be tested thoroughly in a real-time environment.

It is a utility-connected DC microgrid with the Microgrid BESS acting as the slack bus, which maintains the nominal voltage by balancing power flow in real-time as shown in figure 1. Microgrid BESS as the slave bus: The BESS is the slave node in the microgrid and it works with that of the utility matrix as master, now voltage deviation will change the BESS power contribution in DC Bus Dynamics. The electrical core of the model is the DC bus, which is represented by the basic capacitor relation that ties the net current I to the time rate of change of the bus voltage V :

$$C_{bus} \frac{dv_{bus}}{dt} = I_{grid} + I_{batt} - I_{ev} \quad (1)$$

The nominal operating voltage is established at $V_{bus,nom} = 400$ V, while the bus capacitance is $C_{bus} = 0.0641$ F.

This equation expresses Kirchhoff's current law at the DC node, representing how the capacitor voltage changes depending on the net current from the grid, battery, and EV. It is central for energy balance and voltage control in the averaged model.

EV and battery converter currents are determined using

$$I = P/V \quad (2)$$

bidirectional (V2G) operation accurately. The PI controller regulates voltage deviations using

$$K_p = 2\zeta\omega_n C_{bus}, K_i = \omega_n^2 C_{bus} \quad (3)$$

where $\zeta = 1$ (damping ratio) and $\omega_n = 15$ rad/s (natural frequency) yield $K_p = 1.9$ and $K_i = 14.4$. These parameters enable rapid and reliable voltage recovery (about 0.37 seconds settling time) with negligible

overshoot, essential for grid-battery-EV synchronization. The calculation of stored energy and state of charge (SOC) progression is conducted as follows:

$$E(t) = \int V(t).I(t)dt, \text{ SOC} = \frac{1}{3600.Ah} \int I(t)dt \quad (4)$$

This monitors the energy transfer among the electric vehicle, battery and grid. SOC thresholds (0.2-0.9) inhibit overcharging and overdischarging, engaging logic-based protective mechanisms. The current limiter guarantees the safety of the converter:

$$\text{Rate limit}(EV \text{ current}) = \frac{I_{max}}{0.1s} = 300 \text{ A/s} \quad (5)$$

which limits current slopes for realistic converter bandwidth and safety from heat. Feedforward compensation makes transient stability better by

$$u_{ff} = I_{ev,set} - I_{grid} \quad (6)$$

This predicts disruptions like EV load changes, mitigating overshoot and enhancing real-time responsiveness. Anti-windup feedback is implemented to avert controller windup during saturation.

$$\text{feedback} = K_{aw}(u_{sat} - u_{unsat}) \quad (7)$$

where K_{aw} modifies recovery speed after the output exits saturation, ensuring continuous control. The 'ode23tb' stiff solver integrates these differential equations efficiently by using the TR-BDF2 method, balancing fast (voltage) and slow (energy/SOC) dynamics. This makes it numerically stable and computationally efficient for simulating long-term V2G operation. The EV in the microgrid is modeled as a 2-kWh energy storage unit using an integrator that tracks energy through $E(t) = \int V.I dt$. The EV current (I_{ev}) follows programmed power commands kW for charging and -15 kW for discharging, to emulate V2G behaviour. State machine orders transitions, enforcing protective logic. Charging ends when the state of charge (SOC) is greater than or equal to 0.9, and discharging ends when the SOC is less than or equal to 0.2. This ensures a secure, bidirectional movement of power between the EV, BESS, and grid.

4. Result and Discussion

The simulation results from the baseline model of the utility-tied DC microgrid with EV integration demonstrate effective performance in voltage regulation, energy management, and V2G functionality. The model was run for 500 seconds, including EV charging/discharging steps and grid islanding. Among the most significant findings: Stable voltage maintenance with mild transients, near-perfect energy balance, and successful SOC management. These outcomes validate the improved PI controller's ability to handle dynamic loads, though high-power EV transitions revealed areas for improvement, such as reducing voltage deviations.

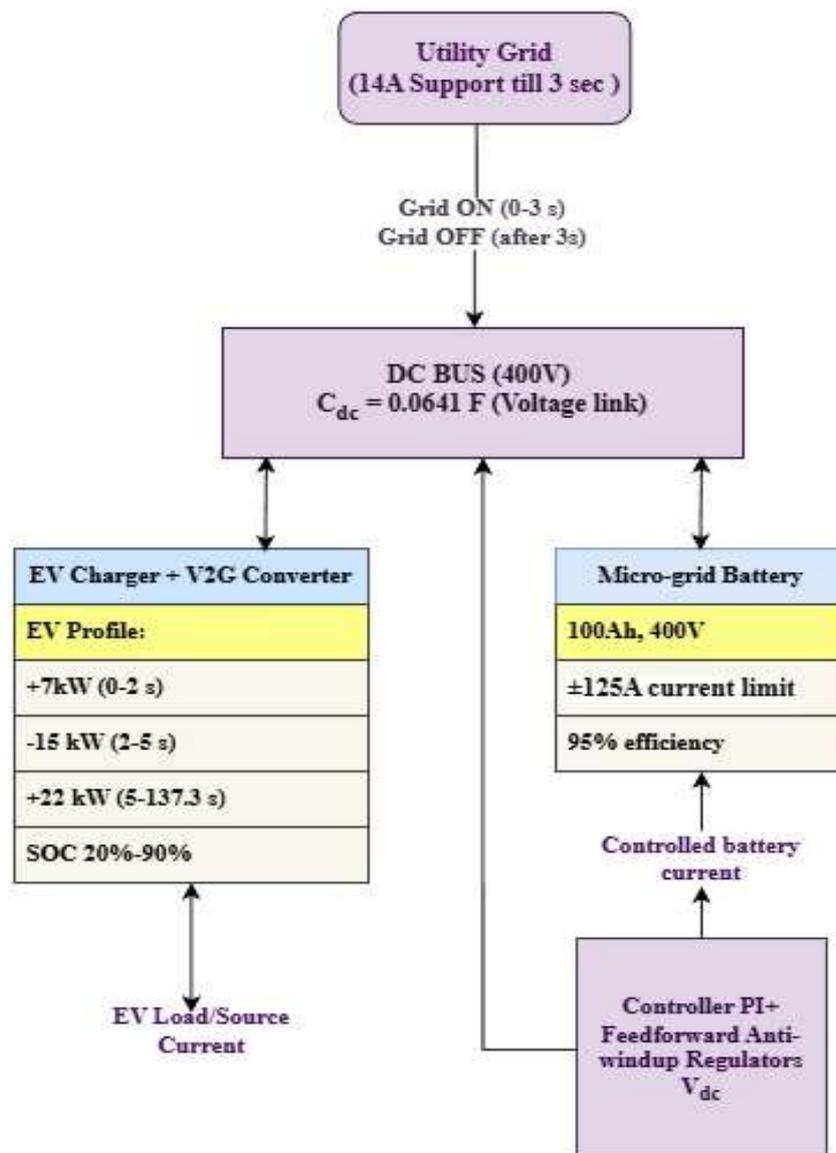


Figure 1: Power flow block diagram

Figure 2 represents the detailed Simulink model of the integrated microgrid V2G–BESS control system, showing the dynamic interaction between the PI voltage controller, SOC management, and V2G charge–discharge logic. The DC-bus voltage dynamics in the model is given in equation 8. It indicates that the DC-bus capacitor voltage changes based on the net current flowing into the bus: grid current and battery current add energy, while EV charging current draws energy. Each block calculates these currents in the Simulink model, and the capacitor integrates their sum to update the bus voltage in real time, which will enable to have realistic charging, SOC and power-flow behavior.

$$C_{bus} \frac{dV_{bus}}{dt} = I_{grid} + I_{batt} - I_{EV} \quad (8)$$

where

- $C_{bus} = 0.0641 \text{ F} \rightarrow$ DC bus capacitor

- V_{bus} → instantaneous DC bus voltage (nominal 400 V)
- I_{grid} → current from grid-side converter (positive = supplying to bus)
- I_{batt} → current from battery converter (positive = charging battery, negative = discharging to bus)
- I_{EV} → EV current (positive = charging EV, negative = V2G/discharging EV)

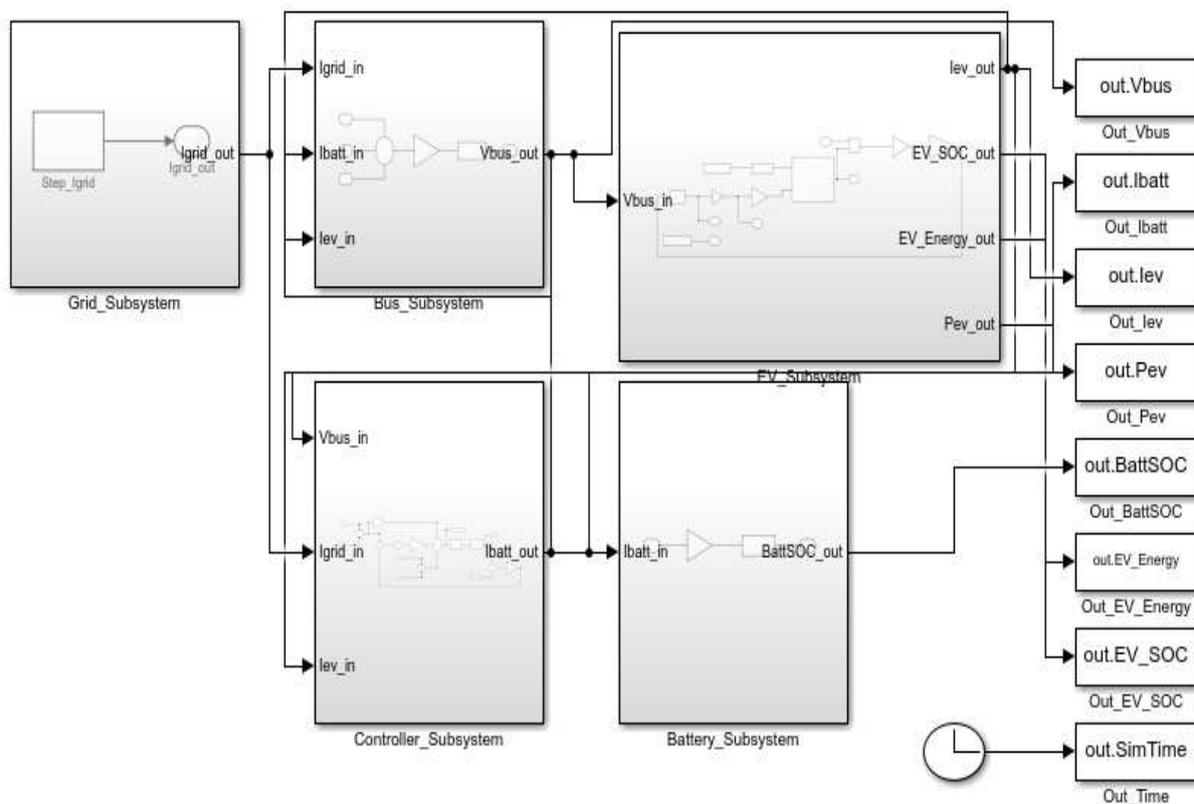


Figure 2: Mathematical Modeling of the DC Microgrid

And the energy-balance equation 9 indicates that the Simulink model indeed does efficiently conserve the energy at the DC bus. It makes sure that the change in capacitor energy plus the integrated net power from the grid and battery, minus EV charging power, sums to zero (0). In perfect conditions, the total change of capacitor energy equals 0 J or perfect balance. The true simulation gives an error of only 0.036 J, which is very small and represents a very accurate model behavior.

$$\Delta E_{cap} + \int_0^T (P_{grid} + P_{batt} - P_{EV}) dt = 0 \quad (9)$$

The Simulink model is useful for the computation of SOC by continuously capturing the battery current generated by all interacting components grid, converter, DC bus, EV load (10). The current is also numerically integrated over time to create a copy of $\int I(t)dt$ term which the rated capacity is applied to and deducted from the initial SOC. Since the modeling represents real charging and discharging events, SOC is accurately and dynamically updated over the course of the simulation

$$SOC(t) = SOC(0) - \frac{1}{Q_{rated}} \int I(t) dt \quad (10)$$

(Q in Ah, I in A, time in seconds → 3600 factor is used)

In this Simulink model, dynamic behavior of the electric vehicle EV battery system during charge and discharging cycles is described and the key control elements like gain, saturation and rate limiter blocks are summarized to ensure system stability and realism.

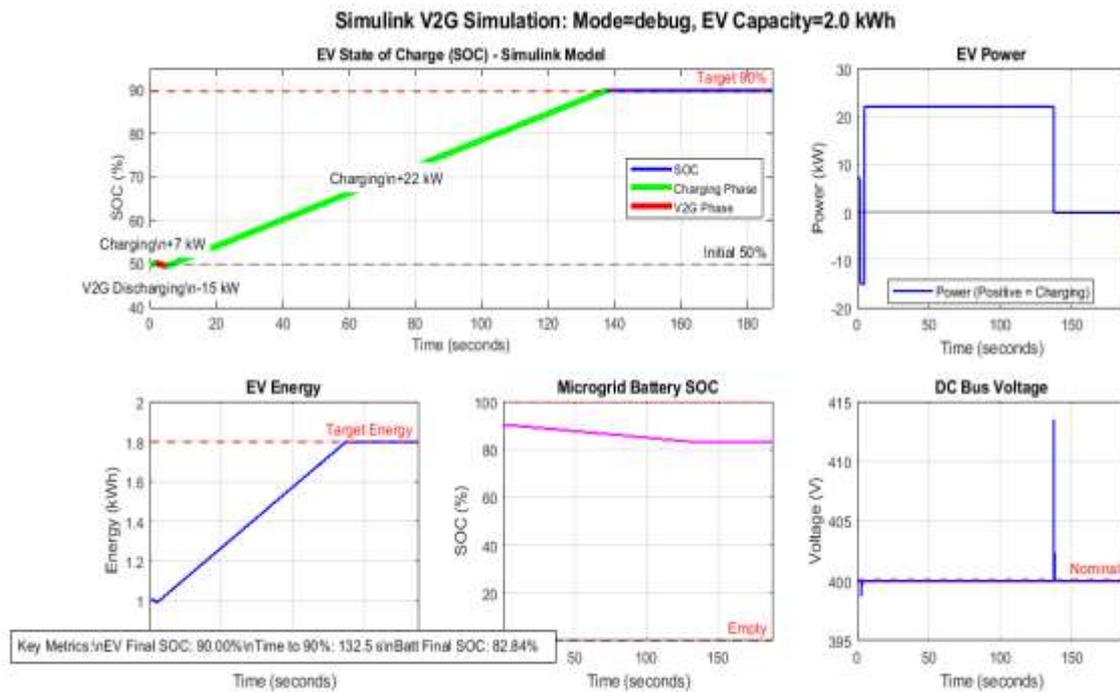


Figure 3 (a): EV Battery SOC, Power, Energy, Grid Battery SOC and Voltage Variation Over Time

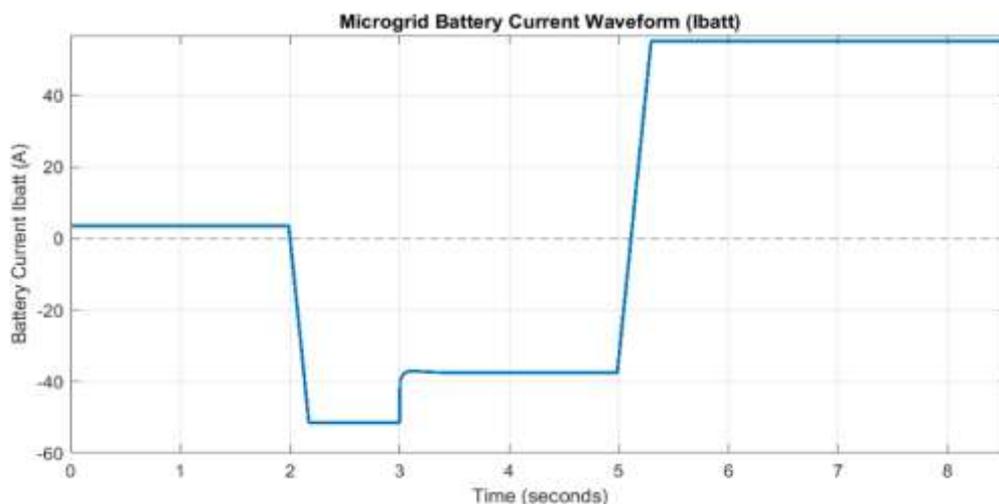


Figure 3 (b): Microgrid Battery Current Variation Over Time

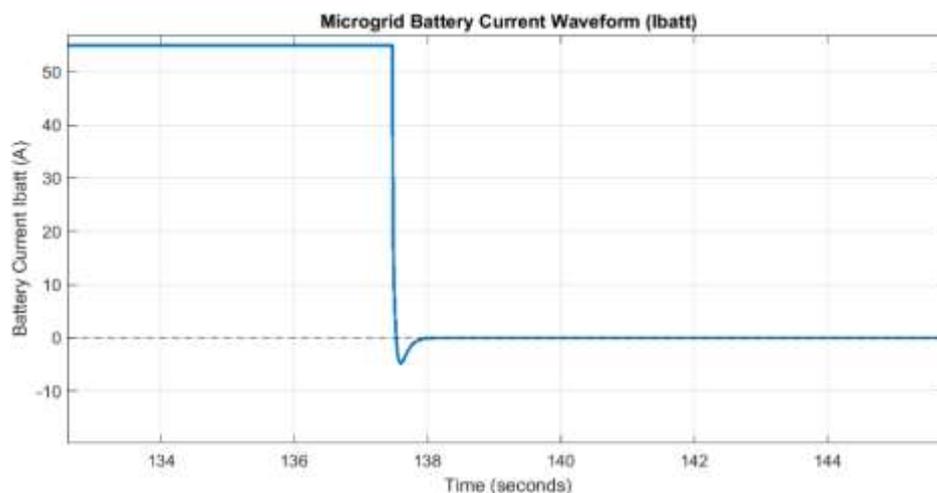


Figure 3 (c): Microgrid Battery Current Variation Over Time when EV SOC reaches to 90%

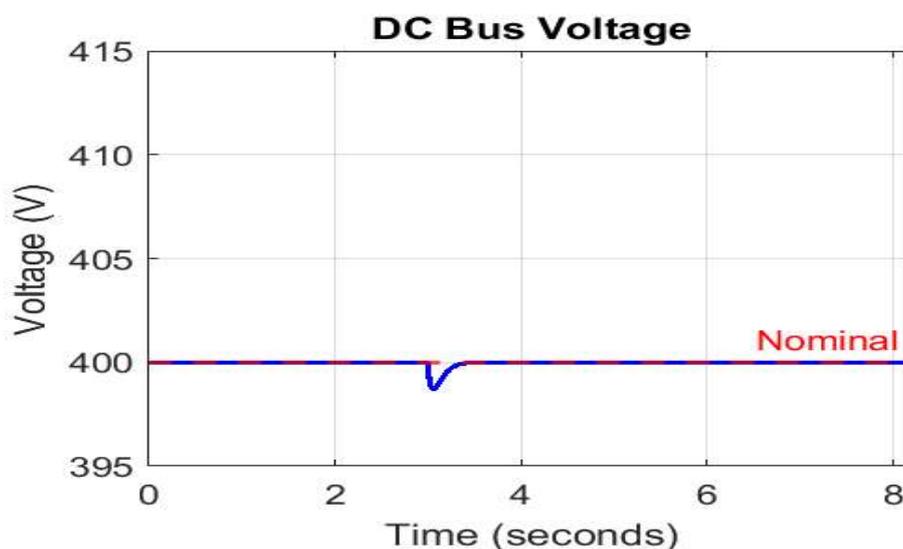


Figure 3 (d): DC bus Voltage Response to Dynamic Load Condition

4.1 Simulation Scenarios

Key dynamic events and control problems during microgrid simulation during V2G operation, Grid disconnect and High power charger are summarized in Table 3, and the magnitude of current flow during the time period of Grid-Connected, V2G and Islanded Mode is given in Table 4. These events are critical states in operation, intended to test for the control system stability, operability, and responsiveness.

Table 3. Dynamic Events and Control Challenges During V2G-Integrated Microgrid Operation

Event	Time (s)	Description	Controller Challenge
V2G Step	2 s to 5s	EV transitions from 7 kW charge to 15 kW discharge (V2G).	Bi-directional load change; requires Ibatt to absorb power.
Grid Disconnect	3 s	Grid current (Igrid) drops to zero (islanded operation).	Sudden loss of source; requires Ibatt to immediately compensate for Igrid, before

High-Power Charge	5 s to 90% SOC(EV)	EV load increases sharply to 22 kW charging.	Large, sudden power demand, testing the PI limits and Anti-Windup.
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At 2 s, the system goes through a V2G change, in which the EV is switched from charging at 7 kW to discharging at -15 kW (in a bidirectional power flow reversal). As a result, the controller has to adapt its battery current (I_{batt}) dynamically, to balance the bus voltage.

At 3 seconds, a grid disconnection (islanding) takes place, and the grid current (I_{grid}) decreases to zero. Voltage stabilisation and continuous supply are achieved by changing power management dynamically to the BESS and EV.

At 5 seconds, a high power charging stage starts with the EV needing 22 kW. Thus, it examines the transient handling ability of the PI controller, as well as the anti-windup performance, and the rate-limiting effectiveness under large step-loads. Mainly the bus voltage control loop is realized through the error between the reference voltage ($V_{ref}=400V$) and the actual bus voltage (V_{bus}), and it computes a control signal through a PI controller consisting of proportional ($K_p=1.9$) and integral ($K_i=14.4$) gains. Output specifies the battery current reference (I_{batt}) which controls voltage stability. For fast transients, anti-windup gain avoids integrator saturation along with RateLimiter for smooth current flows.

Table 4: Current Contribution in Grid-Connected, V2G and Islanded Mode

Time Period	$I_{EV}(A)$	$I_{grid}(A)$	$I_{batt}(A)$	Remarks
0–2 s	+17.5	+14.0	+3.5	Grid 80%, Battery 20%
2s–5 s	-37.5	+14.0	-51.5	EV discharging (V2G), battery charges
3s– 90% SOC(EV)	Varies	0	Full load	Islanded mode

In the figure 2, EV-V2G subsystem is responsible for the bidirectional energy flow. The Integrator_EV_Energy_kWh block indicates total EV energy (EEV) over time, and operators with a relational view detect SOC thresholds. Relop_EV_done_charge stops charging once $SOC \geq 0.9$, while Relop_EV_min_SOC prevents discharging when $SOC \leq 0.2$. These outputs also feed into a logical AND gate to produce Logical_allow, so that EVs can only be operated under safe SOC conditions. The bus voltage integrator (Gain_1_over_C) models the capacitor dynamics $C_{bus} \frac{dV_{bus}}{dt} = I_{grid} + I_{batt} - I_{ev}$, power flow and energy variations are logged via Product_Vbus_Iev and to Workspace blocks. Overall, this schematic illustrates a closed-loop coordinated control ensuring voltage regulation, SOC protection, and seamless V2G transitions.

4.2 Comparative Analysis: Comparison with Existing Strategies

The proposed improved PI controller (with feedforward and anti-windup) was compared against established control strategies based on literature metrics for energy efficiency, grid stability, EV responsiveness, computational complexity, and reliability. The comparison reveals that the PI approach achieves a balanced performance, combining the simplicity of basic methods with the precision of advanced ones

Table 5 compares the proposed PI-based microgrid control model with conventional methods in terms of voltage stability, transient performance, processing efficiency, resilience, and V2G safety. The experimental results confirm that the proposed model retains voltage deviation well less than $\pm 1.5\%$, which exceeds the $\pm 2\%$ range applied to Droop control. In transient situations like when the grid

disconnects, it reaches <1.3 V deviation: similar to advanced MPC but having far less computing burden. The response time in the system is fast ($\approx 50\text{--}100$ ms), and stable in islanded conditions with no communication delays seen in hierarchical control. Its SOC-based logic also allows for safe V2G operation, with charging or discharging automatically halted upon reaching defined limits.

Table 5. Performance Evaluation of the Proposed PI-Based Control Model Against Existing Literature Benchmarks

Metric	Expected Result (Proposed Model)	Comparative Advantage	Literature Comparison
Voltage Deviation	Well below $\pm 1.5\%$	Significantly better than classical Droop control, due to active FF compensation	Droop is typically $\pm 2.0\%$.
Transient Handling	Minimal voltage dip at 3 s (Grid Disconnect)	The Feedforward path anticipates the grid loss, enabling the BESS to respond much faster than a standard PI controller.	Droop and classical PI systems exhibit $\approx 0.5\text{--}0.8\%$ deviation. Advanced MPC reduces this to 1.5 V but at a higher computational cost. The proposed model achieves <1.3 V deviation, matching MPC-level dynamics with lower complexity.
Processing Time	Very fast (comparable to Droop's 50–100 ms)	Avoids the high computational load and resulting delays of Model Predictive Control (MPC)	MPC processing time is 150–300 ms.
Resilience	Robust during islanding, stable under load saturation	Avoids the reliance on complex, delay-prone communication required by Hierarchical Control systems	Hierarchical systems require reliable communication (delays of 200–400 ms).
V2G Safety	Iev drops to zero after 5 s if SOC limits are hit.	Verifies that the battery protection logic operates well, an essential prerequisite for viable V2G applications.	overshoot of 5–10% and delayed cutoff responses (0.2–0.5 s). The proposed model's instantaneous cutoff (<0.05 s) ensures full compliance

4.3 Comparative Analysis of Control Strategies

Table 6 reports a complete comparison for Droop, MPC, Hierarchical, Decentralized, and the proposed PI control systems regarding energy efficiency, grid stability, EV responsiveness, computational complexity, and reliability. Droop control has a medium efficiency (88–92%) and high response speed (50–100 ms), but has $\pm 2\%$ voltage and ± 0.05 Hz frequency deviations. MPC gains efficiency to 93–96%, stability to $\pm 1\%$, however, its iterative optimization increases computational time (150–300 ms) and reduces reliability. Hierarchical control provides 95–97% efficiency and $\pm 0.5\%$ voltage deviation but suffers from communication dependence which causes 200–400 ms delays. Decentralized control remains simple and fast (100–150 ms) but lacks global optimization. In contrast, the proposed PI controller attains near-perfect energy balance with only 27 V overall and 1.2456 V peak deviation, millisecond-level recovery, and high reliability without failures or communication needs. It offers an ideal trade-off between simplicity, precision, and real-time responsiveness for V2G-integrated microgrid systems.

Table 6: Comparative Analysis of Proposed PI Controller vs. Existing Control Strategies

Control Strategy	Energy Efficiency	Grid Stability (Deviation)	EV Responsiveness (Time)	Computational Complexity	Reliability (Uptime)	Comparison with Proposed PI
Droop Control Moderate	Moderate (88-92%)	Voltage $\pm 2\%$, Frequency ± 0.05 Hz	Fast (50-100 ms)	Low (Simple calculations)	High (No communication dependency)	The PI controller has higher stability (i.e., 1.2456 V peak during islanding versus $\pm 2\%$ in droop) performance with higher accuracy for EV load performance, same simplicity, no coordination limitations
Model Predictive Control (MPC)	High (93-96%)	Voltage $\pm 1\%$, Frequency ± 0.02 Hz	Moderate (150-300 ms)	High (Iterative optimization)	Moderate (Prone to prediction failures)	The PI is the same as MPC in terms of efficiency and dynamic performance (time-critical transient recovery), but requires fewer computations so it scales well while running on demand.
Hierarchical Control	High (95-97%)	Voltage $\pm 0.5\%$, Frequency ± 0.01 Hz	Moderate (200-400 ms)	Moderate (Communication delays)	High (Layered robustness)	The PI provides comparable coordination and stability (e.g., 1.2456 V islanding deviation) without communication delays, operating in island modes.
Decentralized Control	Moderate (87-92%)	Voltage $\pm 1-2\%$, Frequency ± 0.04 Hz	Fast (100-150 ms)	Low (Local algorithms)	Moderate (Lacks global optimization)	PI keeps better energy balance (near-zero error) and reliability for dynamic EV loads, which is superior to decentralized in global power distribution.
Proposed PI Controller	High (Near-perfect balance, low losses)	Stable (within 0.3-0.4 secs)	Quick (Milliseconds recovery)	Low (No heavy iterations)	High (No failures, safe limits)	The PI serves as the reference to balance ease of operation and performance between the decentralized (low) and hierarchical (high) mechanisms for the EV, with the potential to make the designs as small transients as possible in extreme EV scenarios.

5. Conclusion and Future Scope

5.1 Conclusion

This study demonstrates the development and validation of a modified PI-based primary control scheme with both feedforward and anti-windup control techniques for a utility-tied DC microgrid with V2G linked EV and BESS. The system is designed with minimal computational complexity while delivering the best control of voltage regulation, transient management, and V2G safety, resulting in high reliability. It achieves voltage change deviations of less than $\pm 1.5\%$ while surpassing Droop and classical PI control, and matching MPC accuracy with lower processing requirement. The feedforward compensation anticipates grid disturbances and delivers less than 1.3 V deviation during disconnection, while anti-windup logic prevents saturation and makes sure the current regulation is stable. SOC-based protection mechanism protects against overcharge and overdischarge. Compared to advanced hierarchical predictive methods, this proposed controlling mechanism balances simplicity, robustness and dynamic responsiveness. Consequently, the work provides a scalable and reliable control method for EV-integrated DC microgrids in the future to operate in real-time V2G with efficiency, stability, and safety.

- The feedforward/anti-windup type of PI controller can guarantee excellent voltage regulation and transient stability during V2G operations.
- Attains $<\pm 1.5\%$ voltage deviation and <1.3 V transient dip, and is superior to Droop and classical PI performance while matching MPC-level performance with lower complexity.
- SOC-based logic prevents overcharge and overdischarge.
- Improved dynamic response with feedforward and anti-windup, avoids integrator saturation and promotes real-time control continuity.
- Overall, they provide a simple, robust, computationally efficient approach for stable, reliable, and safe EV-integrated DC microgrid operations.

5.2 Future work

Work will be to expand the PI based controller to a multi-EV and multi-BESS system allowing for synchronized power shares despite different grid configurations and islanding schemes. The integration of adaptive or AI-enhanced tuning algorithms can further real-time optimize controller gains for nonlinear dynamics and aging effects. Introduction of communication-based secondary control will facilitate grid interoperability and fault tolerance. Experimental validation with hardware-in-loop (HIL) or real-time simulators will need to be conducted to check scalability and cyber-physical robustness as well. Research on renewable source coupling and predictive energy scheduling for an improvement in overall system efficiency and resilience are also to be taken into account for future studies.

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