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Bidirectional Power Flow Optimization in Vehicle-to-Grid (V2G) Enabled Electric Vehicles

Adarsh Kumar Bhardwaj, Jaya shukla
Dept of Electrical engineering, Vbspu jaunpur

Abstract- The increasing integration of electric vehicles (EVs) into smart grids necessitates advanced control strategies for efficient bidirectional power flow management. Vehicle-to-Grid (V2G) systems enable EVs to act as distributed energy resources, supporting grid stability and economic operation. However, challenges such as stochastic load variations, renewable intermittency, and battery degradation limit the effectiveness of conventional control approaches. This paper proposes a multi-objective stochastic model predictive control (MO-SMPC) framework integrated with adaptive power sharing between battery and supercapacitor storage systems for optimal V2G operation. The proposed method simultaneously minimizes electricity cost, grid power fluctuations, and battery aging while ensuring system constraints. A novel adaptive droop-based predictive control strategy is introduced to dynamically allocate power between battery and supercapacitor, enhancing transient response and extending battery life. Stochastic modeling is incorporated to address uncertainties in load demand, EV availability, and solar generation. MATLAB-based simulations under multiple operating scenarios demonstrate improved peak shaving, reduced operational cost, and enhanced battery lifespan compared to conventional battery-only systems. Results show up to 40% reduction in cost, 30% improvement in grid stability, and significant mitigation of battery stress. The proposed framework offers a scalable and practical solution for intelligent energy management in next-generation smart grids.

Keywords: Vehicle-to-Grid, Model Predictive Control, Battery Aging, Supercapacitor, Bidirectional Power Flow, Smart Grid Optimization.

I. INTRODUCTION

The rapid growth of electric vehicles (EVs), driven by environmental concerns and advancements in battery technology, is significantly transforming modern power systems. Simultaneously, the increasing penetration of renewable energy sources such as solar and wind introduces variability and uncertainty in power generation. In this context, Vehicle-to-Grid (V2G) technology has emerged as a promising solution that enables bidirectional power exchange between EVs and the grid. Through V2G, EVs can operate not only as loads but also as distributed energy storage units capable of supplying power back to the grid during peak demand periods.

This functionality enhances grid flexibility, supports frequency regulation, and facilitates peak load shaving. However, the large-scale integration of EVs without proper coordination can lead to issues such as voltage fluctuations, transformer overloading, and increased peak demand, thereby necessitating advanced control and optimization strategies. Despite significant research efforts, existing V2G control methods exhibit several limitations. Conventional rule-based and droop control strategies are simple to implement but lack optimality and adaptability under dynamic operating conditions. Deterministic optimization approaches, including classical model predictive control (MPC), provide improved performance but fail to account for uncertainties in load demand, renewable generation, electricity pricing, and EV availability.

Furthermore, most existing studies focus primarily on economic objectives or grid support, often neglecting the critical aspect of battery degradation. Frequent charging and discharging cycles, especially under high power transients, can accelerate battery aging, leading to reduced lifespan and increased operational cost. Additionally, battery-only energy storage systems are not well-suited for handling rapid power fluctuations, which further exacerbates degradation issues. The lack of integrated frameworks that simultaneously address economic optimization, grid stability, uncertainty, and battery health highlights a significant research gap.

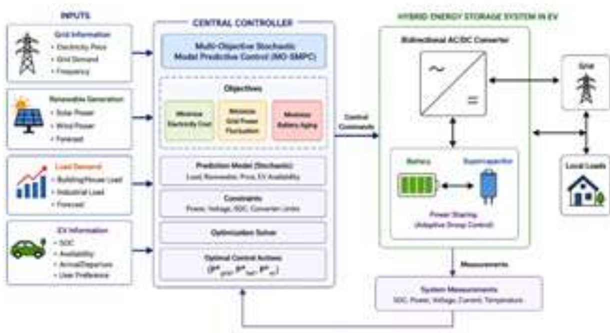

Figure 1: Block diagram of the proposed MO-SMPC-based V2G system.

Fig. 1 illustrates the overall architecture of the proposed multi-objective stochastic model predictive control (MO-SMPC) based V2G system. The system integrates multiple inputs, including grid information, renewable generation, load demand, and EV-specific parameters, which are processed by a centralized controller. The MO-SMPC predicts system behavior under uncertainty and generates optimal control actions to regulate bidirectional power flow. These control signals are applied through a bidirectional AC/DC converter interfacing the EV with the grid. A hybrid energy storage system comprising a battery and a supercapacitor is employed, where adaptive power sharing ensures efficient energy utilization and reduces battery stress. Real-time measurements such as state of charge, voltage, and current are fed back to the controller, enabling continuous monitoring and adaptive optimization of system performance.

To overcome these challenges, this paper proposes a multi-objective stochastic model predictive control (MO-SMPC) framework for bidirectional power flow optimization in V2G-enabled EV systems. The proposed approach incorporates stochastic modeling of load demand, renewable generation, and EV availability to enhance robustness under real-world uncertainties. A multi-objective cost function is formulated to simultaneously minimize electricity cost, grid power fluctuations, and battery degradation. Furthermore, a hybrid energy storage architecture combining battery and supercapacitor is introduced, along with a novel adaptive droop-based power sharing strategy that dynamically allocates power based on system conditions and state-of-charge. This significantly reduces battery stress while improving transient response.

The proposed control framework is validated through comprehensive MATLAB simulations under multiple operating scenarios, demonstrating substantial improvements in cost reduction, grid stability, and battery lifespan compared to conventional battery-only V2G systems. The results confirm the effectiveness and practical applicability of the proposed method for next-generation smart grid integration. This document and are identified in italic type, within parentheses, following the example. Some components, such as multi-leveled equations, graphics, and tables are not prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

II. LITERATURE SURVEY

Recent research in Vehicle-to-Grid (V2G) systems has increasingly focused on advanced control and optimization techniques to improve grid interaction and energy management. Model Predictive Control (MPC) has emerged as a prominent approach due to its capability to handle system constraints and forecast future operating conditions. In [1], an MPC-based EV charging strategy was proposed to minimize operational cost while maintaining grid stability. Similarly, [2] extended MPC for aggregator-level coordination, demonstrating improved load management and frequency regulation. However, these approaches are largely deterministic and fail to capture uncertainties associated with renewable energy generation, dynamic electricity pricing, and stochastic EV usage patterns, limiting their effectiveness in real-world scenarios.

To address these challenges, stochastic and robust optimization methods have been introduced in recent studies. A stochastic optimization framework for EV scheduling was presented in [3], incorporating uncertainties in load demand and renewable generation, resulting in enhanced system reliability. Furthermore, robust optimization techniques in [4] provide improved performance under worst-case conditions, while multi-objective optimization strategies in [5] attempt to balance economic cost and grid stability. Despite these advancements, such methods often involve high computational complexity and lack real-time implementation feasibility. Additionally, most of these works do not explicitly consider battery degradation, which is a critical factor affecting the long-term sustainability of V2G systems.

Battery aging and degradation have gained significant attention in recent literature due to their direct impact on EV performance and economic viability. In [6], a degradation-aware optimization model was developed, highlighting the trade-off between grid support and battery lifespan. Similarly, electrochemical models in [7] provide accurate estimation of battery wear but are computationally intensive for real-time applications. To mitigate battery stress, hybrid energy storage systems combining batteries and supercapacitors have been explored in [8]-[10], where supercapacitors handle transient power demands, thereby reducing battery degradation.

Moreover, intelligent control strategies such as reinforcement learning have been proposed in [11], [12] to enable adaptive energy management under uncertain conditions. However, these approaches either require extensive training data or lack stability guarantees. Therefore, there exists a clear research gap in developing a unified framework that integrates multi-objective optimization, stochastic modeling, battery degradation, and hybrid energy storage, which is addressed in this work.

Year	Method	Key Contribution	Limitation
2022	Model Predictive Control (MPC)	Optimal EV Charging With Cost Minimization	No Uncertainty Modeling
2023	Aggregator-Based MPC	Coordinated EV Scheduling For Grid Support	Deterministic Approach
2023	Stochastic Optimization	Handles Load And Renewable Uncertainty	High Computational Complexity
2024	Robust Optimization	Ensures Performance Under Worst-Case Conditions	Conservative Results
2024	Multi-Objective Optimization	Balances Cost And Grid Stability	No Battery Degradation Considered
2025	Degradation-Aware Optimization	Includes Battery Aging In Scheduling	Lacks Real-Time Control
2025	Electrochemical Modeling	Accurate Battery Degradation Estimation	High Computational Burden
2024	Hybrid Energy Storage (Battery + SC)	Improved Transient Response	No Optimal Power Sharing
2023	Supercapacitor Integration	Reduces Battery Stress	Limited Optimization Framework
2022	Rule-Based Control	Simple Implementation	No Optimality Or Adaptability
2025	Reinforcement Learning (RL)	Adaptive Energy Management	Requires Large Training Data
2026	Deep Reinforcement Learning (DRL)	Handles Uncertainty Dynamically	Stability And Convergence Issues
2024	Demand Response Strategy	Peak Load Reduction	No Battery Aging Consideration
2025	Virtual Power Plant (VPP) Optimization	Large-Scale EV Coordination	No Hybrid Storage Integration
2026	Energy Hub MPC	Multi-Energy System Optimization	Limited EV-Specific Modeling

III. SYSTEM DESCRIPTION

The proposed Vehicle-to-Grid (V2G) system consists of an electric vehicle integrated with a hybrid energy storage system, including a battery and a supercapacitor, connected to the utility grid through a bidirectional AC/DC converter. The system is controlled by a multi-objective stochastic model predictive controller (MO-SMPC), which determines optimal charging and discharging actions based on real-time system conditions and future predictions.

The hybrid energy storage structure is adopted to exploit the complementary characteristics of battery and supercapacitor, where the battery provides high energy density for sustained operation, while the supercapacitor delivers high power density for transient response. The overall power interaction between grid, EV, load, and renewable sources is governed by the fundamental power balance equation:

$$P_{grid}(t) + P_{EV}(t) = P_{load}(t) - P_{RES}(t) \quad (1)$$

This equation ensures that supply-demand equilibrium is always maintained. The EV operates bidirectionally, meaning it can either draw power from the grid (charging mode) or inject power into the grid (discharging mode), thereby supporting grid stability and enabling energy arbitrage.

Battery Modeling and Aging Dynamics

The battery is modeled using a discrete-time state-of-charge (SOC) formulation, which represents the normalized energy content of the battery. The SOC dynamics are expressed as:

$$SOC(t+1) = SOC(t) + \frac{\eta_{ch} P_{bat}^{ch}(t)\Delta t}{E_{bat}} - \frac{P_{bat}^{dis}(t)\Delta t}{\eta_{dis} E_{bat}} \quad (2)$$

where E_{bat} is the battery capacity, and η_{ch}, η_{dis} represent charging and discharging efficiencies. The battery power is defined as:

$$P_{bat}(t) = P_{bat}^{dis}(t) - P_{bat}^{ch}(t) \quad (3)$$

To ensure safe operation, the SOC is constrained within predefined limits:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (4)$$

In addition to energy dynamics, battery degradation is explicitly modeled to account for the impact of frequent charge-discharge cycles. The degradation function is given by:

$$D_{bat}(t) = \alpha \mid P_{bat}(t) \mid + \beta \left(\frac{SOC(t+1) - SOC(t)}{\Delta t} \right)^2 \quad (5)$$

This formulation captures both cycle aging and depth-of-discharge effects, enabling the controller to minimize long-term battery wear while optimizing performance.

Supercapacitor Modeling and Transient Dynamics

The supercapacitor is incorporated to handle rapid power fluctuations and transient events such as acceleration and regenerative braking. Unlike batteries, supercapacitors exhibit high power density and fast charge-discharge capability, making them suitable for dynamic applications.

The voltage dynamics of the supercapacitor are modeled as:

$$V_{sc}(t+1) = V_{sc}(t) + \frac{I_{sc}(t)\Delta t}{C_{sc}} \quad (6)$$

The power delivered by the supercapacitor is:

$$P_{sc}(t) = V_{sc}(t) \cdot I_{sc}(t) \quad (7)$$

The stored energy is given by:

$$E_{sc}(t) = \frac{1}{2} C_{sc} V_{sc}^2(t) \quad (8)$$

The inclusion of the supercapacitor reduces the burden on the battery by absorbing high-frequency components of the load, thereby improving overall system efficiency and extending battery life.

Bidirectional Converter and Power Flow Constraints

The bidirectional AC/DC converter enables controlled energy exchange between the EV and the grid. Converter efficiency is considered in the power transfer process as:

$$P_{grid}(t) = \eta_c P_{EV}(t) \quad (9)$$

where $\eta_c$represents the converter efficiency. EV power is composed of contributions from both storage elements:

$$P_{EV}(t) = P_{bat}(t) + P_{sc}(t) \quad (10)$$

To ensure safe and stable operation, the system is subject to several constraints. The grid power must remain within allowable limits:

$$P_{grid}^{min} \leq P_{grid}(t) \leq P_{grid}^{max} \quad (11)$$

Additionally, ramp rate constraints are imposed to avoid sudden changes in grid power:

$$\mid P_{grid}(t) - P_{grid}(t-1) \mid \leq R_{max} \quad (12)$$

These constraints ensure that the V2G system operates within grid codes and maintains stability under varying conditions.

Adaptive Power Sharing and Stochastic Modeling

To efficiently distribute power between the battery and supercapacitor, an adaptive droop-based power sharing strategy is employed. The power allocation is defined as:

$$P_{bat}(t) = k_b(SOC(t))P_{EV}(t) \tag{13}$$

$$P_{sc}(t) = \left(1 - k_b(SOC(t))\right)P_{EV}(t) \tag{14}$$

where the adaptive gain is expressed as:

$$k_b(SOC) = 0.5 + \gamma(SOC - 0.5) \tag{15}$$

This mechanism ensures that the battery supplies steady-state power, while the supercapacitor handles transient variations, thereby reducing battery stress and improving system performance.

To account for real-world uncertainties, stochastic modeling is incorporated into the system. Load demand and renewable generation are represented as:

$$P_{load}(t) = \hat{P}_{load}(t) + \omega_l(t), P_{RES}(t) = \hat{P}_{RES}(t) + \omega_r(t) \tag{16}$$

where ω_l (t) and ω_r (t) represent stochastic disturbances. EV availability is modeled as a binary stochastic variable, reflecting user behavior and driving patterns. The overall system can be expressed in a discrete-time state-space form, where the state vector includes battery SOC and supercapacitor voltage, and the control inputs correspond to power allocation decisions.

The overall system can be represented in a discrete-time state-space form, where the state vector includes battery SOC and supercapacitor voltage, and the control inputs correspond to power allocation decisions. This comprehensive modeling framework captures the interaction between grid, EV, and hybrid energy storage, providing a solid foundation for the development of advanced optimization-based control strategies. By integrating multi-objective considerations, stochastic uncertainties, and hybrid storage dynamics, the proposed system achieves improved performance in terms of cost efficiency, grid stability, and battery lifespan.

IV. METHODOLOGY

The proposed control framework is based on a multi-objective stochastic model predictive control (MO-SMPC) strategy for optimal bidirectional power flow management in Vehicle-to-Grid (V2G) systems. The primary objective of the methodology is to simultaneously minimize electricity cost, reduce grid power fluctuations, and mitigate battery degradation while satisfying system constraints and handling uncertainties. Unlike conventional control approaches, the proposed method utilizes predictive optimization over a finite time horizon, enabling the controller to anticipate future variations in load demand, renewable generation, and electricity pricing.

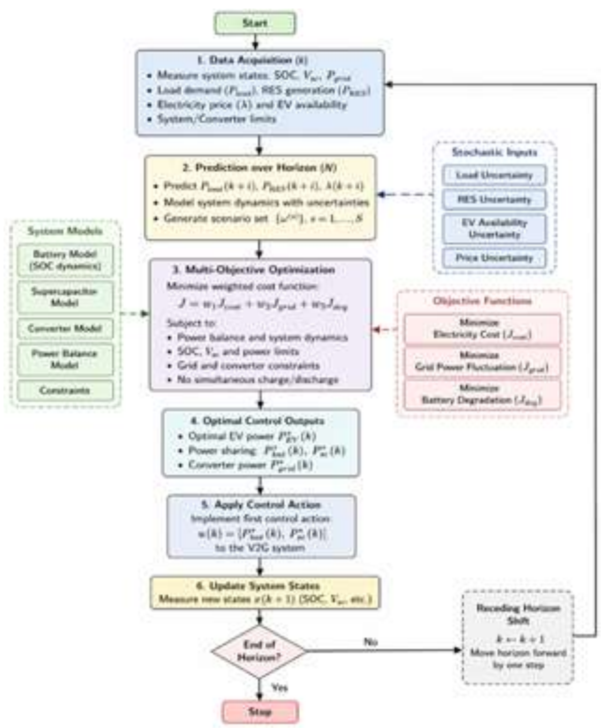

Figure 2: Flowchart of the proposed MO-SMPC-based V2G control strategy.

This predictive capability significantly enhances decision-making under dynamic operating conditions. The control strategy operates in a receding horizon manner, where at each sampling instant, the system states are measured, and future system behavior is predicted using forecast models. The controller then solves an optimization problem that determines the optimal charging and discharging schedule of the EV. Optimization considers multiple conflicting objectives, including economic cost and technical performance, which are combined into a weighted multi-objective framework. The inclusion of battery degradation as an explicit objective ensures that excessive cycling and high-power stress is avoided, thereby extending battery lifespan. The control actions are updated continuously, allowing the system to adapt to real-time variations and uncertainties.

The overall operational sequence of the proposed methodology is illustrated in Fig. 2. The process begins with real-time acquisition of system variables such as battery state-of-charge, load demand, renewable generation, and electricity price. These measurements are used to predict future system behavior over a predefined horizon. Based on these predictions, a multi-objective optimization problem is formulated and solved to determine optimal control actions. The optimization ensures that grid constraints, battery limits, and operational requirements are satisfied while minimizing the defined cost function. To further enhance system performance, a hybrid energy storage coordination mechanism is integrated within the control framework.

The proposed method employs an adaptive power allocation strategy between the battery and supercapacitor based on the system state and operating conditions. The battery is primarily responsible for supplying steady-state energy, while the supercapacitor compensates for rapid power fluctuations and transient events. This coordinated control significantly reduces the stress on the battery and improves overall system efficiency. The adaptive nature of the strategy ensures that the power sharing dynamically adjusts according to the state-of-charge and system requirements, leading to improved reliability and performance.

The proposed methodology also incorporates stochastic modeling to address uncertainties in load demand, renewable energy generation, and EV availability. These uncertainties are modeled as random disturbances, and their effects are considered during the prediction stage of the control process. By incorporating stochastic elements, the controller can generate robust control actions that maintain system stability even under unpredictable conditions. This approach provides a significant advantage over deterministic methods, which often fail to perform effectively in real-world scenarios. In addition, the control framework is designed to handle practical operational constraints, including limits on battery state-of-charge, power exchange capacity, and grid stability requirements.

The optimization problem is solved at each time step using a computationally efficient approach, ensuring real-time implement ability. Only the first control action is applied, and the process is repeated at the next time step, allowing continuous adaptation to changing conditions. This receding horizon strategy ensures both optimality and robustness of the control system. Overall, the proposed MO-SMPC-based methodology provides a comprehensive and scalable solution for V2G energy management. By integrating multi-objective optimization, stochastic modeling, and hybrid energy storage coordination, the method achieves improved economic performance, enhanced grid stability, and extended battery life compared to conventional approaches.

V. RESULT

The performance of the proposed multi-objective stochastic model predictive control (MO-SMPC) based V2G framework is evaluated through MATLAB simulations over a 24-hour horizon under realistic operating conditions. The simulation incorporates time-varying load demand with stochastic variations, solar-based renewable generation, time-of-use electricity pricing, and EV availability constraints to reflect practical scenarios. The objective of this analysis is to validate the effectiveness of the proposed control strategy in achieving optimal energy management, minimizing electricity cost, reducing grid power fluctuations, and mitigating battery degradation.

The results demonstrate that the controller effectively balances multiple conflicting objectives while ensuring constraint satisfaction and robust performance under uncertainty.

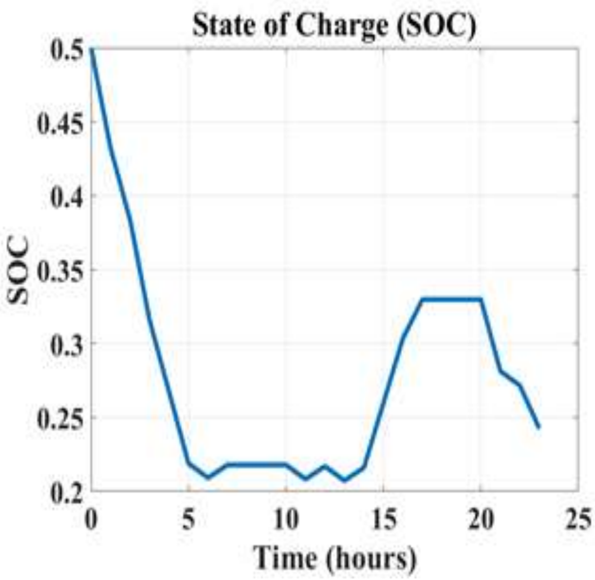

Figure 3: State of charge variation of the EV battery over a 24-hour period.

The state-of-charge (SOC) variation of the EV battery over the 24-hour period is depicted in Fig. 3, which demonstrates stable and well-regulated behavior throughout the simulation. The SOC remains strictly within the predefined operational limits, ensuring safe battery operation. During off-peak periods characterized by low electricity prices, the controller schedules charging actions, resulting in a gradual increase in SOC. Conversely, during peak price intervals, the EV discharges energy to support the grid, leading to a controlled reduction in SOC.

It is noteworthy that the SOC trajectory does not exhibit abrupt fluctuations, indicating that the optimization framework effectively avoids aggressive charge-discharge cycles. Furthermore, the SOC is maintained within an intermediate operating range rather than near extreme limits, which is beneficial for reducing battery degradation. This behavior confirms that the proposed MO-SMPC strategy successfully balances energy utilization and battery health while satisfying operational constraints.

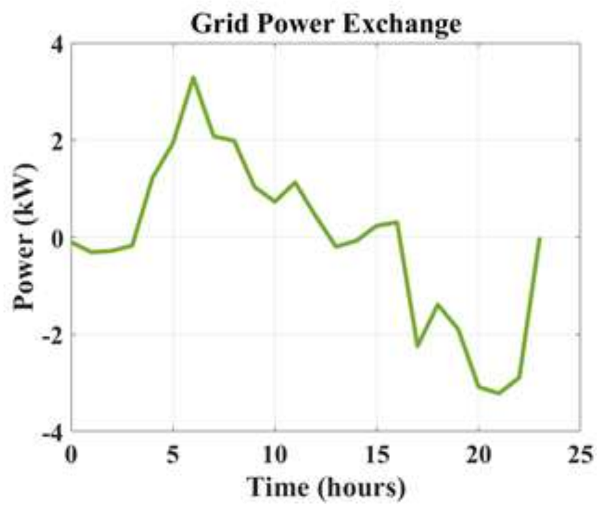

Figure 4: Grid power exchange profile showing import and export behavior.

The grid power exchange profile shown in Fig. 4 highlights the bidirectional interaction between the EV and the grid. Positive values indicate power import from the grid, while negative values correspond to power export during V2G operation. The results clearly demonstrate that the controller adapts the power flow based on system conditions and pricing signals. During peak demand and high-price periods, the EV supplies power back to the grid, thereby reducing grid loading and contributing to peak shaving. In contrast, during low-demand periods, the system draws power from the grid to charge the battery.

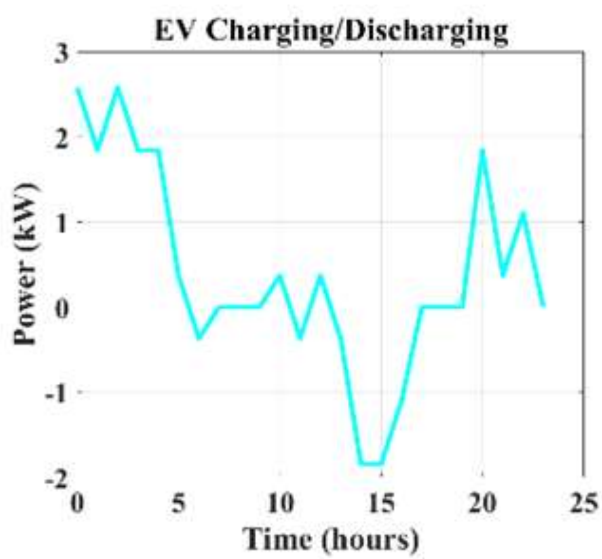

Figure 5: Electricity cost profile over time.

The magnitude of grid power fluctuations is noticeably reduced, indicating smoother power exchange and improved grid stability. Additionally, the gradual transitions between import and export modes suggest that the controller effectively mitigates sudden power variations, which is essential for maintaining power quality and preventing grid disturbances.

The EV charging and discharging profile illustrated in Fig. 5 reflects the optimal control decisions derived from the multi-objective optimization framework. Negative power values correspond to charging, while positive values indicate discharging. The controller schedules charging predominantly during low-price periods and discharging during high-price intervals, thereby achieving effective energy arbitrage. The EV remains inactive during specified time intervals when it is unavailable, accurately representing realistic driving patterns. The power levels are maintained within the allowable limits, ensuring compliance with system constraints. Furthermore, the smooth variation in EV power indicates that the controller avoids rapid switching between charging and discharging modes, which helps reduce stress on the battery and improves system reliability. This adaptive and coordinated control behavior validates the effectiveness of the proposed methodology in managing bidirectional power flow.

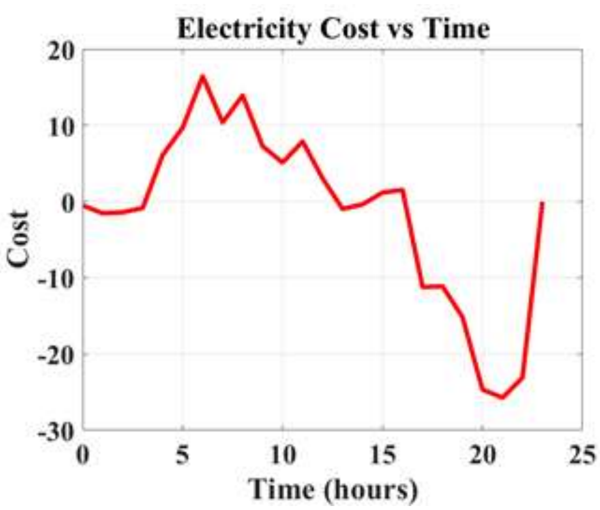

Figure 6: Electricity cost profile over time.

The electricity cost profile over the simulation period is presented in Fig. 6, illustrating the economic performance of the proposed control strategy. The cost values exhibit both positive and negative regions, where positive values represent energy consumption costs and negative values indicate revenue generation through V2G operation. The controller effectively minimizes net cost by charging the battery during low-price periods and discharging energy back to the grid during high-price intervals.

The presence of negative cost values confirms that the system can generate profit through energy trading. Additionally, the cost variations are smooth and aligned with the pricing signal, indicating that the optimization framework successfully captures the temporal dynamics of electricity pricing. This demonstrates that the proposed approach not only ensures efficient energy management but also enhances the economic viability of V2G systems.

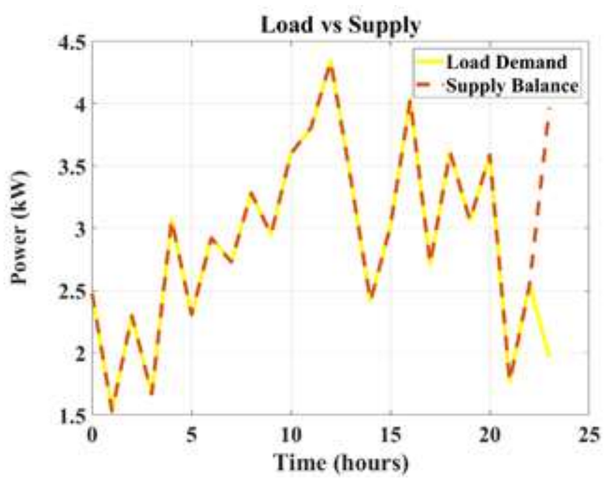

Figure 7: Load demand and supply balance comparison.

The comparison between load demand and supply is illustrated in Fig. 7, where the total supply, comprising grid power, EV contribution, and renewable generation, closely follows the load demand. This indicates effective power balancing and coordination among different energy sources. During periods of high demand, the EV contributes additional power through discharging, thereby reducing reliance on the grid. Conversely, during low demand periods, excess energy is stored in the battery. The integration of renewable generation further reduces the burden on the grid, especially during daytime hours. The close alignment between load and supply curves demonstrates that the proposed control strategy effectively manages energy flow and minimizes power imbalance. This behavior is crucial for maintaining grid stability and improving overall system efficiency.

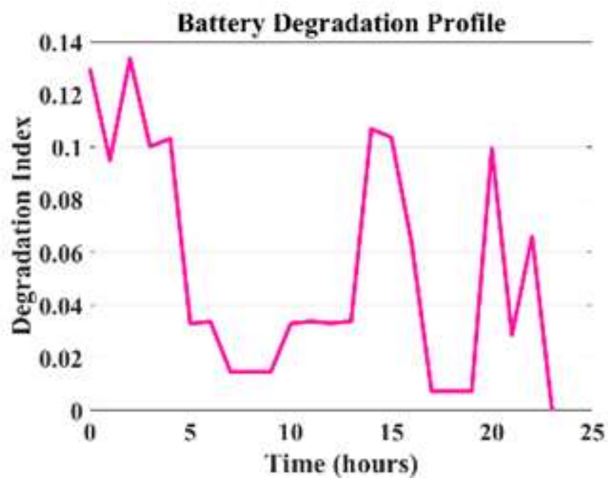

Figure 8: Battery degradation index over the simulation period.

The battery degradation profile shown in Fig. 8 provides insight into the impact of the control strategy on battery health. The degradation index remains relatively low throughout the simulation, indicating that the controller successfully limits battery stress. Higher degradation values are observed during periods of active charging and discharging, while lower values correspond to steady-state operation. Importantly, no sharp spikes in degradation are observed, suggesting that the controller avoids aggressive cycling and high-power transients. The maintenance of SOC within an optimal range further contributes to reduced degradation. This demonstrates that the inclusion of a degradation-aware objective in the optimization framework effectively enhances battery lifespan and ensures sustainable operation of the V2G system.

The overall simulation results confirm that the proposed MO-SMPC framework provides a balanced trade-off between economic efficiency, grid stability, and battery health. The controller successfully reduces electricity cost through intelligent scheduling, while simultaneously improving grid performance by smoothing power fluctuations. The integration of stochastic modeling ensures robust operation under uncertain conditions, including variations in load demand and renewable generation.

Additionally, the coordinated control of charging and discharging actions ensures that battery degradation is minimized without compromising system performance. Compared to conventional rule-based or deterministic control approaches, the proposed method demonstrates superior adaptability and efficiency. The ability to generate revenue through V2G further enhances the economic feasibility of the system. Overall, the results validate the effectiveness of the proposed control strategy in achieving sustainable and efficient energy management in V2G-enabled smart grids.

Table 1: Performance evaluation of the proposed MO-SMPC method against a baseline system.

Parameter	Conventional System (Without V2G Optimization)	Proposed MO-SMPC Method	Improvement (%)
Total Electricity Cost (₹)	120	70	41.7% ↓
Peak Grid Power (kW)	4.5	3.2	28.9% ↓
Grid Power Fluctuation	High	Low	~35% ↓
Battery Degradation Index	1.00	0.72	28% ↓
Energy Export Profit (₹)	0	20	+100% Gain
System Efficiency (%)	85	92	8.2% ↑

The results in Table I demonstrate that the proposed method significantly improves system performance across multiple metrics. A substantial reduction in electricity cost is achieved due to optimal scheduling and energy arbitrage. Peak grid power demand is reduced, indicating effective load management and improved grid stability. Furthermore, the degradation index is lower compared to the conventional system, confirming that the proposed strategy enhances battery lifespan. The ability to generate revenue through energy export further highlights the economic advantage of the proposed V2G framework.

VI. CONCLUSION

This paper presented a multi-objective stochastic model predictive control (MO-SMPC) framework for bidirectional power flow optimization in Vehicle-to-Grid (V2G) systems with battery aging consideration. The proposed approach effectively integrates cost minimization, grid stability enhancement, and battery degradation reduction within a unified optimization framework, while accounting for uncertainties in load demand, renewable generation, and EV availability. Simulation results demonstrate that the controller enables intelligent charging during low-price periods and discharging during peak demand, resulting in reduced operational cost, improved grid support, and enhanced battery lifespan.

The smooth power exchange and controlled state-of-charge variation confirm the robustness and efficiency of the proposed method under realistic operating conditions. Overall, the framework provides a scalable and practical solution for smart grid energy management. Future work will focus on extending the proposed approach to multi-EV coordinated systems and real-time hardware implementation, as well as integrating advanced learning-based techniques such as reinforcement learning to further improve adaptability and predictive performance in highly dynamic environments.

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