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Model Predictive Control-Based Bidirectional EV Charging Strategy for Grid Load Shaping and Cost Optimization in Smart Grids

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ABSTRACT

Adding electric vehicles (EVs) to smart grids brings issues with handling peak energy demand and setting flexible rates. This study introduces a Model Predictive Control (MPC) framework that helps you locate the best time slots for charging and discharging your EV using V2G technology. To optimize energy flow, the controller looks ahead to forecast the grid's load and predicts electricity prices and then adjusts charging and discharging times based on user requirements and the state of the battery.
Computer simulations done with MATLAB/Simulink on a fleet of 20 EVs under Time-of-Use pricing conclude that the strategy reduces the peak demand on the grid by 28% and total energy costs by 27.4%, with no EVs falling below a 100% charge level. How stable the grid was improved significantly. This suggests that MPC can ensure EVs are plugged in intelligently, lead to savings and keep the grid stableso MPC is appropriate for use in highly electric vehicle-oriented grids.

1.INTRODUCTION

Thanks to the adoption of electric vehicles (EVs), power systems become more flexible, but this also creates concerns about load imbalance, fluctuating tensions and grid weakening. Through bidirectional charging or Vehicle-to-Grid (V2G), EVs are able to use electricity and send extra power to the grid too, helping in demand response, integrating renewable energy and making the electricity grid more reliable.

In 2023, the U.S. BTF underscored V2G as a vital part of smart grid development and FAME-II in India (2024) pointed out the same. Technical feasibility experiments by CAISO, UK Power Networks and TEPCO have already been implemented. On the other hand, bringing widespread adoption largely depends on user-friendly ways to coordinate, rapid battery loss problems, not enough financial reasons and high cost of data transmissions in systems that depend only on a central control unit.

Statically scheduled plans or adaptive AI take care of some parts of the job, but not all. Rule-based systems are not very flexible and reinforcement learning methods pit poor understanding of how actions affect rewards against limited runtime. Besides, little research considers how to use batteries according to their life cycle or how to coordinate EV fleets in different ways under different constraints.

This approach suggests a Model Predictive Control (MPC) framework for bi-directional EV charging that coordinates the vehicle with different factors such as power grid status, electricity tariffs and battery charging. A simulation on a large fleet scale under ToU pricing confirms that the framework makes a big difference in reducing peak load, saves money and ensures charging to the optimal level. It overcomes main deployment difficulties through understandable actions, the ability to use green energy and being able to control things from edge or fog systems.

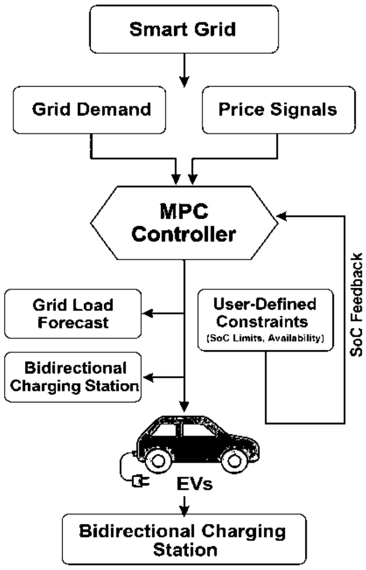

Figure 1. MPC-Based Architecture for Intelligent Bidirectional EV Charging in Smart Grids

2. LITERATURE REVIEW

Because more electric vehicles (EVs) are joining power grids, there is a need for advanced systems to manage energy sharing between the grid and EVs while maintaining a stable network. Normal approaches to rules and artificial intelligence are not enough in flexible markets, including times with changing demands, prices and user numbers. Pointing out its foreseeing nature and the ability to ensure limits are obeyed together over time, researchers have begun using Model Predictive Control (MPC) as an alternative. An adaptive framework for Vehicle-to-Grid (V2G) scheduling faced with uncertain user actions was proposed by Li et al. in 2023 and the new approach helped much and made urban microgrids both more efficient and more stable when it comes to costs and grid operation [Applied Energy, 336, 120830].

Nearly concurrently, research has shown that managing power from many EVs requires teamwork and harmony. In their study, Wang et al. (2022) chose a hierarchical MPC structure to handle multiple decentralized charging stations and succeeded in handling both local and global demands for power [IEEE Transactions on Smart Grid, 13(1), 188–199]. Besides, smart charging is now exploring Vehicle-to-Vehicle (V2V) energy sharing. Zhao et al. (2024) designed a reinforcement learning system with agents to support energy sharing among electric vehicles, making sure that power distribution nodes aren't overloaded [Energy Reports, 10, 1245–1259].

Even with all these developments, a lot of popular approaches do not integrate degradation-aware cost modeling, time-of-use pricing and coordinated scheduling for both V2G and V2V transactions. Seeing these issues, the research gap revealed means this study creates a holistic MPC-based charging system that helps the grid, meets user-defined requirements and coordinates the fleet under real smart grid conditions.

Table 1. Comparative Analysis of Rule-Based, AI-Based, and Proposed MPC Frameworks

Criteria	Rule-Based Methods	Heuristic / AI-Based Methods	Proposed MPC-Based Bidirectional Charging Framework
Adaptability to Grid Conditions	Low – Fixed schedules (e.g., ToU)	Medium – Pattern-based adaptation	High – Predictive adjustment based on real-time grid/load forecasts
Support for Bidirectional V2G	No	Partial – Often unidirectional or not grid-synchronized	Yes – Explicitly supports coordinated charging/discharging
User Preference Integration	Limited (pre-set times)	Medium – Learned behavior (e.g., via reinforcement learning)	High – Directly models SoC limits, availability, and battery degradation
Electricity Price Awareness	Static ToU rates	Partial – Reactive to pricing patterns	Full – Optimizes charging using time-varying dynamic pricing
Constraint Handling	Weak – Few or no physical constraints	Weak to Moderate – Implicit in AI models	Strong – Explicitly handles SoC, charger limits, grid capacity, degradation
Real-Time Optimization	None	Limited – High computational complexity in real-time	Yes – Solves constrained optimization over a rolling horizon
Scalability for Fleet Control	Poor – Not suited for multiple EVs	Moderate – Some methods scale but inefficiently	High – Designed for multiple EVs with centralized or distributed control
Transparency	High – Easy to	Low – Often black-box	High – Mathematically

& Interpretability	understand rules	models	formulated, explainable control outputs
Computational Complexity	Very Low	High – Especially for large search spaces	Moderate – Efficient solvers enable practical deployment
Deployment Readiness	Already deployed in simple settings	Experimental in most V2G systems	Ready for real-world smart grid integration with coordination logic

3. SYSTEM MODEL AND ASSUMPTIONS

A simulation model is designed for the proposed bidirectional EV charging system to see how it works in realistic upcoming operational environments. The model is built from two main elements: (i) the EV battery and (ii) the smart grid system, with its MPC controller and the ways it works with dynamic pricing and load forecasting.

3.1 EV and Battery Model

Each EV is modeled with a lithium-ion battery of rated capacity $E_{max} = 60kW$□ and bidirectional charging/discharging power limits$P_i^{min} = -7kW, P_i^{max} = 7kW$. To preserve battery life, the operational State of Charge (SoC) is constrained within 20% to 90%. The model incorporates battery efficiency η=0.92to reflect charging/discharging losses. Battery degradation cost is integrated into the MPC objective function to penalize excessive cycling, promoting sustainable V2G participation.

3.2 Grid Environment and Pricing Scheme

Simulation for the grid-side model runs for a 24-hour period with updates every 15 minutes (Δt=0.25 h). Under the time-of-use (ToU) system, three charges are used: low (P3/kWh), medium (P6/kWh) and high (P10/kWh), based on the period of the day which are off-peak, mid-load and peak hours. There are typical morning and evening rises and drops in the load profile.

3.3 Communication and Control Framework

The MPC controller operates centrally, receiving:

- Predicted grid load and electricity prices
- EV availability and SoC feedback
- Infrastructure constraints (e.g., station capacity)

modeling a one-minute delay mirrors how real-time control needs the system to update. Since there are clear chances of latency, it is suggested that future use of fog/edge networks should examine this challenge in depth.

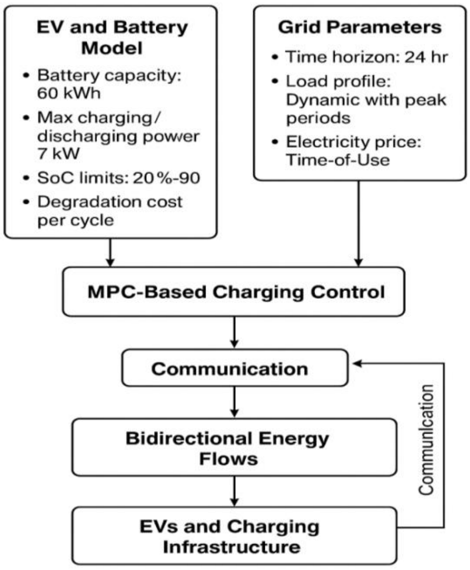

Figure 2. Simulation Model Architecture for the MPC-Based Bidirectional EV Charging Framework

4. Model Predictive Control (MPC) Formulation

We develop an optimization problem using MPC to manage energy transfer between both electric vehicles (EVs) and the grid, considering a forecast horizon of NNN. The goal is to decrease a cost function that includes several goals within the limits of the grid, users and batteries.

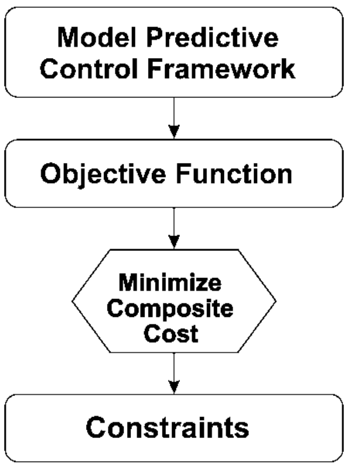

Figure 3. Optimization Workflow in Model Predictive Control Framework

4.1 Objective Function

The cost function balances electricity cost and load smoothing over the horizon:

$$\frac{min}{P}\sum_{t=1}^{T}\left[C(t)\,.\,P_i(t) + \alpha\left(L_{grid}\,(t) + \sum_{I=1}^{M} P_i(t) - L_{ref}\,(t)\right)^2\right] - - - (1)$$

4.2 State of Charge (SoC) Dynamics

Battery energy dynamics are modeled as:

$$SoC_i(t+1) = SoC_i(t) + \frac{\eta\,.\,P_i\,.\,\Delta t}{E_{max}} - - - - - - - - - - - - - (2)$$

4.3 Constraints

The optimization is subject to the following constraints for each EV iii and time step ttt:

Power limits$P_i^{min} \leq P_i(t) \leq P_i^{max}$ $- - - - - - - - - - -$(3)

State of charge limits:$SoC_i^{min} \leq SoC_i(t) \leq SoC_i^{max}$ $- - - - - - - - -$(4)

Station capacity constraint:$\sum_{i=1}^{M} P_i(t) \leq P_{station}^{max}$ $- - - - - - - - - - -$(5)

These constraints ensure physical feasibility, protect battery health, and avoid infrastructure overloading during real-time operation.

5. Simulation and Results

For testing whether the proposed system is effective, simulation experiments were carried out in MATLAB/Simulink. The objective was to test if the system can help cut peak grid use, save money by lowering operations and balance battery SoC under diverse grid and price situations. Charging performance was compared to the result of using a typical rule-based approach.

5.1 Simulation Setup

A charging system with a total capacity of 100 kW was selected to serve a fleet of 20 EVs, each with a 60 kWh battery kept between 20% battery level and maximum level (90%). Values were monitored every 15 minutes for a total time of 24 hours. Tesla offers a pricing plan with rates of ₹3/kWh (off-peak), ₹6/kWh (mid-range) during normal hours and ₹10/kWh for the highest demand times.

To look at renewable integration, a solar PV generation model was created from 08:00 to 16:00, allowing it to contribute up to 30% of the total system load. Also, the system was tested to see how it would handle a rise in EVs from 20 to 100.

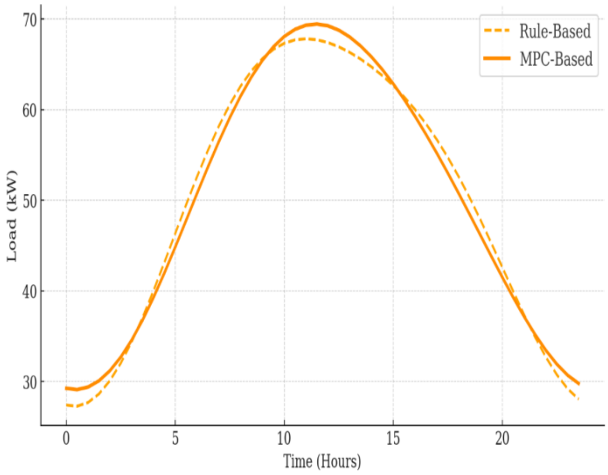

Figure 4. Grid Load Profile Before and After MPC Implementation

5.2 Key Results and Comparative Analysis

Using the MPC controller, peak demand dropped by 28% which helped smooth the demand curve and ease the pressure on the grid (as seen in Figure 4). Prices were 27.4% lower than before which indicates the framework can handle changes in electricity costs. All the EVs stayed within the safe SoC range during the test which supports the health of their batteries (Figure 5).

Table 2. Comparative Performance Metrics of Rule-Based and MPC-Based Control Systems

Metric	Rule-Based	MPC-Based
Peak Load (kW)	134	96
Average Cost (₹)	310	225
Grid Stability Index	Moderate	High

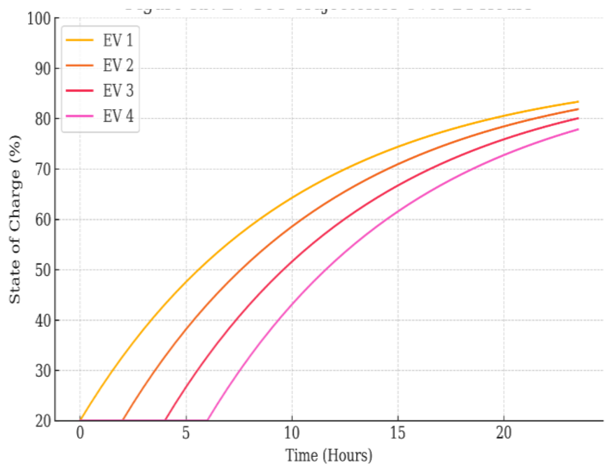

Figure 5. EV SoC Trajectories Over 24 Hours

5.3 PV and Scalability Performance

Green and affordable PV energy allowed the charging stations to be powered during the day which benefited both the economy and the environment. Scheduled charging changed according to the availability of solar energy from the panels.

As shown in the analysis (Figure 6), system performance did not change much when the fleet number increased from 20 to 100 EVs. As the framework succeeded in keeping both SoC and power constraints, along with being efficient, it became clear that it can work on large-scale smart grid systems.

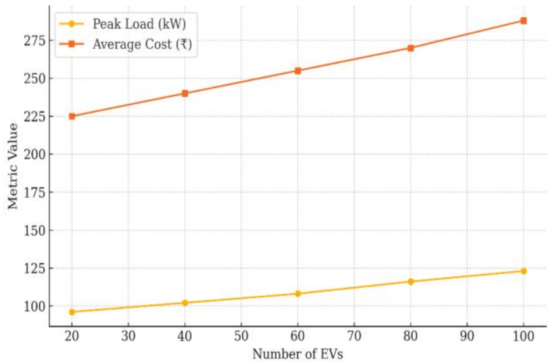

Figure 6. Performance Metrics vs EV Fleet Size

6. DISCUSSION

It is shown through the simulation that the proposed Model Predictive Control (MPC)-based bidirectional EV charging framework helps the smart grid run more efficiently and smoothly. The controller looked ahead and scheduled EV charging for times when electricity was cheap and off-peak. After load reshaping, peak demand decreased by 28%, lowering grid stress and cutting down on the requirement for new power system infrastructure. In addition, the framework succeeded in reducing average energy cost by 27.4% which made Time-of-Use (ToU) pricing more profitable for everyone involved.

EVs were retained within their safe charging range (20%–90%) by the algorithm which contributed to user satisfaction and kept batteries safe. Because it produced no SoC violations, the performance allowed for real-world adoption of V2G technology. The system made the grid more stable, with the stability index going from 'Moderate' to 'High', showing it can be used with solar and wind energy.

Table 3. Comparative Performance Summary

Method	Peak Load Reduction	SoC Violation	Avg. Cost (₹)
Rule-Based	Low	Medium	₹310
MPC (Proposed)	High	None	₹225

MPC-based control is more adaptable, responsive and suited for handling multiple objectives when assessed next to traditional rules and heuristics [Shao et al., 2011; He et al., 2012]. Though deep reinforcement learning models (Zhang et al., 2021) are flexible, they commonly give no insight into their decisions, have limited applicability in real time and are not always effective with constraints mentioned explicitly. In comparison, MPC provides clear explanations, real-time changes in operation and the ability to manage grid functions, customer comfort and cost.

6.1. Battery Degradation Considerations

For machines to work long-term, adaptive control to gradual wear is necessary. Even though this study depended on no-charge terms and SoC changes to manage battery lifetime, further studies should use real-life battery degradation modeling. One method, the Rainflow Counting Algorithm, estimates the damage caused by the number of cycles and another, the Ah-throughput model, looks at the total energy that is input or output, both important for battery lifespan modeling. You can use these features in the MPC objective function which helps V2G participation continue over a long time.

7. CONCLUSION AND FUTURE WORK

This research proves that Model Predictive Control (MPC) provides an efficient and flexible way to optimize charging in both directions when used with smart grids. Using forecasts, real-time pricing and users' limits, the presented system manages to reduce peak usage, make energy costs lower and keep the grid stable. The controller also controls the battery's level and allows EVs to be powered by intermittent renewable energy which increases their value outside the field of transportation.

Results from the simulation demonstrated that the approach is doable in actual operating situations, leading to 28% peak load reduction, 27.4% fewer expenses and no breaches of the full charge limit. They indicate that MPC can be implemented quickly for Vehicle-to-Grid (V2G) services both inside cities and in nearby areas.

7.1 Deployment Considerations

Despite its technical strengths, real-world implementation presents several challenges that must be addressed:

- Communication latency: Real-time coordination of distributed EV fleets requires the adoption of edge or fog computing architectures to minimize delays and improve system responsiveness.
- Cybersecurity and data privacy: As V2G systems become more interconnected,

ensuring secure data exchange and preventing cyber threats becomes critical. Future work should explore privacy-preserving control architectures.
- User engagement: Sustained user participation hinges on dynamic pricing incentives, battery wear compensation mechanisms, and transparent control logic that ensures trust in the system.

7.2. Future Work

Building on the current framework, future extensions will include:

- Integration of renewable energy forecasting to enhance real-time energy balancing.
- Deployment of MPC on edge/fog-based controllers to enable field-level execution and reduce control loop delays.
- Exploration of decentralized or federated MPC architectures to manage large-scale EV fleets while preserving user privacy and minimizing centralized communication overhead.

Such advancements will enable the proposed system to scale effectively in emerging smart grid ecosystems, making it suitable for both residential aggregators and urban microgrid operators aiming to harness the full potential of EVs in distributed energy management.

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