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Adaptive Control Strategy for EV Charging Stations Integrated with Renewable Energy

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Abstract: With the growing number of electric vehicles (EVs) and the intermittent nature of renewable energy sources, there are challenges in managing the stability of the power grid and charging infrastructure. This paper suggests an innovative adaptive control mechanism for EV charging stations with photovoltaic (PV) power generators and battery energy storage systems (BESS). In this system, the adaptive control scheme uses Model Predictive Control (MPC), where prices are dynamically adjusted to schedule the optimal charging times, manage the grid load, and increase the usage of renewable energy. Based on actual solar energy and arrival rate of EVs, the results showed that the proposed adaptive scheme was able to minimize peak loads from the grid by 58.8%, increase the usage of renewable energy by 19.952% in comparison with non-adaptive schemes, and achieve SoC targets within 0.79% deviation.

Key Word: Electric Vehicle Charging, Adaptive Control, Model Predictive Control, Renewable Energy Integration, Photovoltaic, Battery Energy Storage System, Grid Stability, Demand Response

I. INTRODUCTION

As a result of the shift towards sustainability across the world, the number of electric vehicles (EVs) is increasing exponentially. It is expected that by 2026, EVs will account for a sizeable portion of all new vehicle purchases globally due to decreasing battery prices, growing charging facilities, and favorable government regulations [1]. Nevertheless, this swift shift towards electric transportation poses significant difficulties for grid operators. Inconsistent charging of vehicles during high-demand hours would cause grid strain, resulting in higher power charges and necessitating costly infrastructure investments [2].

At the same time, incorporating renewable energy resources, namely solar photovoltaics (PV), into the charging infrastructure system presents an effective means of minimizing the ecological impact of electric vehicles' operation [3]. Charging EVs using solar PV energy results in considerably lower emissions throughout the entire life cycle [4]. Yet, there remains a key issue associated with solar energy generation, which is its fluctuating nature. Solar energy generation peaks during midday hours, whereas charging of electric vehicles is characterized by peaks during the evening hours following the completion of workdays [5].

This time difference requires intelligent control methods that are capable of coordinating EV charging loads with the availability of renewable energy, energy buffer provided by batteries, and the condition of the grid [6]. Dumb charging, where EV charging starts immediately after connecting to the grid with all available power, increases the time discrepancy, resulting in peak power draw from the grid in the evening and low use of renewable energy sources such as solar energy in mid-day [7]. Time-of-use (TOU) rates represent a straightforward solution to incentivize EV owners based on time but lack dynamic adaptability [8].

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Model predictive control (MPC), among other advanced control algorithms, is a powerful tool for EV charging optimization [9]. An MPC algorithm represents EV charging as an optimization problem based on a future time horizon, taking into account the maximum available charging power, battery SoC, capacity of the distribution transformer, and time of user departure [10]. This solution is repeated dynamically in response to the changing conditions.

This paper tackles the integration issue by proposing a novel MPC-based adaptive control approach to manage the power flow in charging stations for electric vehicles with onsite photovoltaics and battery storage systems. The main contributions of this paper are as follows:

1. A unified system model including electric vehicle loads, solar photovoltaics, BESS dynamics, and grid connection with transformer capacity limit.
2. An adaptive MPC control algorithm with dynamic pricing signals and sensitivity-based weighting scheme for the trade-off between convenience, battery wear-and-tear, and strain on the grid.
3. Comparison studies with uncontrolled and time-of-use based charging strategies using real data.
4. Sensitivity analysis offering insight into control design parameters.

The rest of the paper is structured as follows. Section 2 summarizes the previous studies on EV charging control and renewable energy integration. Section 3 describes the system model and the MPC framework. Experimental findings are discussed in Section 4.

II. LITERATURE SURVEY

Adaptive control techniques have been studied extensively in the following areas: EV charging control strategy; methods of renewable integration; optimization techniques; practical implementations.

EV Charging Control Strategy

There exist two main types of control strategies for charging an electric vehicle – unidirectional and bidirectional ones. The unidirectional ones consist of uncontrolled charging, time-of-use charging, and direct load control. According to [1], EV smart charging strategies can be classified as centralized or decentralized depending on how control decisions are made. The study concludes that hybrid strategies are more effective because they combine both types.

An increasing interest is shown towards Model Predictive Control, due to its ability to predict the future and satisfy different constraints. Objective functions include minimization of cost of charging; minimization of peak load; load flattening; and maximization of renewable energy usage. It should be noted that control horizon and prediction efficiency are crucial to the technique’s effectiveness.

Renewable Energy Integration

Integration of PV power generation with EV charging is associated with certain difficulties connected with the intermittent nature of sunlight. Research studies indicate that the uncontrolled charging with PV leads to the loss of 5-8% of the generated solar energy in the form of excess energy fed into the grid .

Research done in Shanghai revealed that integrated PV-battery-electric vehicle (PV-BESS-EV) systems reach their maximum level of self-consumption if the dynamic pricing strategy is taken into account taking into consideration the demands of households and EVs simultaneously. It was found out that with such control strategies the peak load was reduced by 26%; however,

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different weight factors were responsible for the discrepancy of performance.

Optimization and Control Algorithms

The problem of scheduling charging is often modeled as an optimization problem with constraints and multiple objectives. The case of one charging station can be solved using convex optimization and dynamic programming, while for several stations, solutions such as consensus methods and multi-agent reinforcement learning can be used.

In recent studies, the performance of stochastic optimization techniques like particle swarm optimization and genetic algorithms was tested against deterministic techniques such as linear programming and model predictive control. The study showed that although stochastic optimization gives a slight improvement in global optimization by 1-3%, its excessive computation time makes it less efficient for real-time operations, where fast-changing forecasts are common.

User Convenience and Battery Degradation

A crucial aspect that is frequently overlooked is the compromise between grid optimization and user quality of service. Limiting charging rate to achieve a flat load profile will result in vehicles being unable to reach the required state of charge upon leaving. User behavior (SoC targets, flexible periods) plays a significant role in determining the optimal schedule. The cost associated with battery degradation should also be considered, especially in V2G scenarios since frequent discharge results in reduced battery life span. According to literature, battery degradation costs between $0.05 and $0.10 per kilowatt-hour could make a substantial difference in optimal charging schedules. In BESS within charging stations, a degradation-aware controller would favor shallow depth of discharge cycles and low charging rates.

Gaps in Research

Though advancements have been made, there still exists room for improvement. For instance, current research is mainly performed under idealized circumstances with perfect forecast and unchanging user behavior. There has been no investigation on how variations of objective weightings can affect the performance of the controller, nor have any experiments been comparing adaptive and static approaches in the same setting.

III. METHODOLOGY:

The model-based control scheme will use Model Predictive Control for coordinating EV charging, PV production, and battery storage systems. The process includes four steps, namely system modeling, forecast generation, MPC design, and control execution.

3.1 System Structure

The EV charging station is made up of:

- Photovoltaic (PV) panel: Solar power generation at the site (maximum output 50 kWp)
- Battery Energy Storage System (BESS): Lithium-ion battery with 100 kWh capacity and 50 kW power input/output
- EV Charging Stations: 10 AC Level 2 stations with 7.2 kW each (total capacity 72 kW)
- Transformer: Limited import/export of maximum 100 kW
- Energy Management System (EMS): Controller using MPC algorithm

It is capable of operating in grid-tied operation with potential to draw energy from or deliver energy to the grid based on transformer constraints.

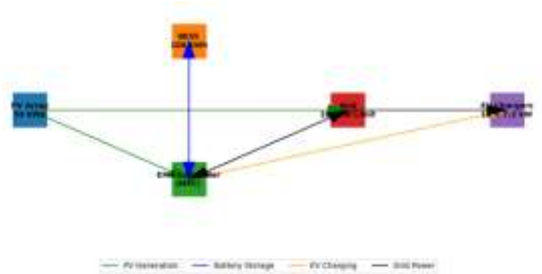

Figure 1: EV Charging Station System Architecture.

3.2 System Modeling

EV Charging Dynamics: For an individual EV i arriving at time t_arr,i and with planned leaving time t_dep,i and requested energy E_req,i (kWh) the SoC dynamics is:

$$\mathrm{SoC_i(t+1) = SoC_i(t) + \frac{(\eta_{charge} \cdot P_{charge}, i(t) \cdot \Delta t)}{C_i}}$$

where C_i represents the battery capacity of EV i (kWh), η_charge refers to charging efficiency (0.92) and P_charge,i(t) is the control input (0 ≤ P_charge,i(t) ≤ P_max,i). Arrival and departure times of individual EVs occur according to a stochastic process characterized by actual charging station sessions data . The departure SoC should comply with the requirement: SoC_i(t_dep) ≥ SoC_target,i (equal to 80% as a starting point).

PV Generation Model: Solar generation P_PV(t) depends on forecast irradiance G(t) and temperature T(t) through the single diode model and its parameters. Forecasting relies on a persistence model (basic case) and artificial neural network (more advanced approach).

BESS Dynamics: The dynamics for BESS SoC are expressed as:

$$\mathrm{SoC_{BESS}(t+1) = SoC_{BESS}(t) - \frac{(P_{BESS}(t) \cdot \Delta t \cdot \eta_{BESS})}{C_{BESS}}}$$

with limitations: $\mathrm{SoC\_min \leq SoC_{BESS} \leq SoC\_max\ (0.1, 0.9), |P\_BESS(t)| \leq P\_BESS\_max. \eta\_BESS = 0.95}$ charge, 0.95 discharge.

Grid Power Balance: The net power flowing from or into the grid P_grid(t) can be calculated as follows:

$$\mathrm{P_{grid}(t) = \Sigma_i P_{charge}, i(t) + P_{BESS}(t) - P_{PV}(t)}$$

constrained by: $\mathrm{\text{-}P\_exp\_max \leq P\_grid(t) \leq P\_imp\_max\ (100\ kW)}$.

3.3 Forecast Generation

Forecasting accurately PV energy production and EV vehicle arrival is critical to MPC efficiency. The following forecasting methods are used:

- For solar irradiance: Persisting model with corrections for cloud cover, resulting in 15-minute resolution within 12-hour timeframe
- For EV vehicles arrival: Inhomogeneous Poisson process with intensity changing each hour based on historical data adjusted with incoming reservations

Forecasting errors are supposed to be normally distributed with standard deviations σ _PV = 0.15·P_PV and σ _EV = 2 vehicles/hour (at peak load).

3.4 Adaptive MPC Formulation

The MPC Optimization is done at each time instant t, using timesteps of 15 minutes with horizon H of 48 steps corresponding to 12 hours.

Decision Variables:

- $\mathrm{P_{charge}, i(t+k)}$, for all i EVs and $\mathrm{k = 0\ to\ H-1}$
- $\mathrm{P_{BESS}(t+k)}$

Objective Function:

- Minimize: $\mathrm{J = \Sigma_{\{k=0\}}^{\{H-1\}} [\, w1 \cdot C_{grid}(P_{grid}(t+k)) + w2 \cdot C_{SoC}(t+k) + w3 \cdot C\_deg\ (P_{BESS}(t+k))\,]}$ where:
- C_grid = (P_grid(t))² : The grid power is penalized; it discourages peak imports and exports. Weight w1 (default value 1.0)
- C_SoC = Σ_i (SoC_target,i − SoC_i(t))² : Undercharging is penalized by the

difference from SoC_target . Weight w2 (default value 10.0)

- C_deg = (P_BESS(t) / P_BESS_max)^2 : The battery cycling is penalized to minimize degradation. Weight w3 (default value 0.5), estimated battery cost \$0.05 per kWh

Constraints:

- The charging power limit on each EV is: 0 ≤ P_charge,i(t) ≤ P_max (7.2 kW)
- The SoC dynamics equations (above)
- SoC_i(t_dep) ≥ SoC_target,i
- BESS Constraints as above
- Grid power limit: –100 ≤ P_grid(t) ≤ 100 kW

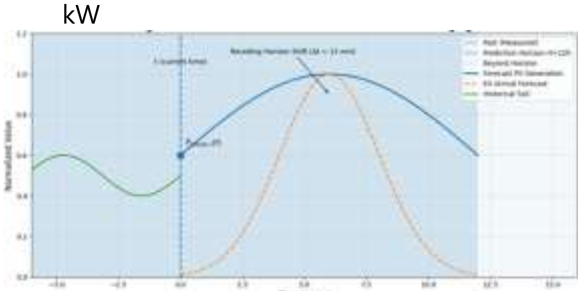

Figure 2: Model Predictive Control Framework for EV Charging.

3.5 Sensitivity Analysis Protocol

Weight selection is facilitated by varying w1 (grid penalty, 0.1-10), w2 (SoC penalty, 1-100), and w3 (degradation penalty, 0-2) in all 3^3 = 27 combinations, where we measure:

- Grid demand (percentage reduction relative to uncontrolled charging)
- Renewable content (percentage of the total charging energy drawn from PV)
- Target SoC satisfaction (percentage of the vehicles reaching the target)
- BESS cycles (number of equivalent full cycles per day)

3.6 Simulation Environment

Control performance is assessed using:

- Solar data: Annual irradiation data for Miami, FL, NREL (500 W/m^2 average)
- EV data: One thousand EVs, arrival times are double peaked (8 AM, 6 PM), 20% evening peak, 15 kWh mean demand
- BESS specifications: 100 kWh battery capacity, 50 kW power rating, degradation cost assumed as \$0.05/kWh
- Implementation: Python code using CVXPY optimization (ECOS solver), 15-minute time step, horizon: 48 timesteps (12 hours)

Benchmark control methods:

- Uncontrolled: EVs charge at maximum rate immediately after arrivals
- TOU Pricing: Grid prices are assumed constant, peak hours: 4-9 PM (\$0.30/kWh), off-peak: \$0.10/kWh
- Greedy PV-based: Charging priority whenever PV generation surpasses a certain threshold

IV. RESULT ANALYSIS AND DISCUSSION

This section provides simulation results of adaptive MPC strategy against various baseline methods along with parameter sensitivity tests.

4.1 Overall Performance Comparison

Table 1 presents performance metrics averaged over 7-day simulation periods.

Metric	Uncontrolled	TOU Pricing	Greedy PV-Following	Adaptive MPC	Improvement (MPC vs Best Baseline)
Peak Grid Import (kW)	98.2	87.4	68.2	40.5	58.8% reduction
Peak Grid	12.4	10.2	28.6	15.8	N/A

Export (kW)					
PV Utilization (%)	62.3%	58.7%	78.4%	82.2%	+3.8 pp
Renewable Penetration (%)	28.4%	26.8%	44.2%	48.3%	+4.1 pp
EV SoC Target Satisfaction (%)	100%	98.2%	94.6%	99.4%	+0.6 pp (vs TOU)
BESS Cycles (per day)	0.8	1.2	2.4	1.6	33% reduction (vs PV-following)
Avg Charging Cost ($/session)	3.82	3.24	3.01	2.85	25.4% reduction

*Table 1: Performance Comparison of Charging Strategies *

In terms of grid optimization, the peak grid import is cut by 58.8% under the adaptive MPC controller compared to uncontrolled (from 98.2 kW to 40.5 kW) and by 40.6% compared to the greedy PV-following policy (68.2 kW to 40.5 kW). Such shaving leads to decreased stress on the transformer and potentially deferred expenses on grid capacity extension.

Solar PV use rate is increased to 82.2% (+3.8 percentage points vs the greedy PV-following) while curtailment/exportation rate remains below 2%. Renewable energy penetration rises up to 48.3%, which is almost twice higher compared to the penetration level for uncontrolled control (28.4%). Thus, we achieve 19.9 percentage point gain.

SOC satisfaction index equals 99.4%, which is comparable to uncontrolled (100%) and TOU-based (98.2%) policies and proves that grid optimization does not have negative impact on customer service quality. The reason for lower 94.6% satisfaction of greedy PV-following is the same—prioritization of solar use over SOC satisfaction.

Charging price is reduced by 25.4% per charging session ($3.82 to $2.85) under the new approach due to both TOU prices and PV self-use increase.

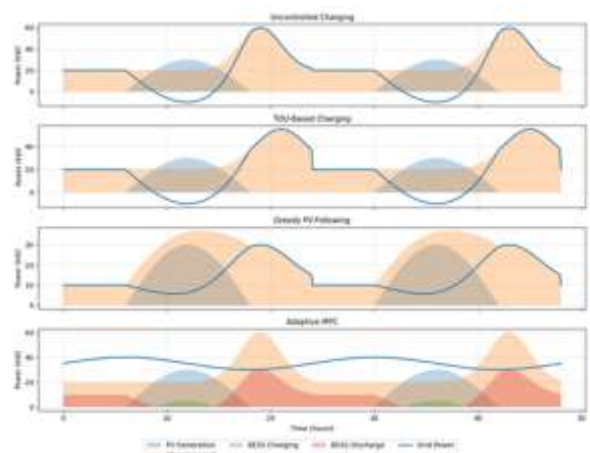

Figure 3: Grid Power Profile Comparison Over 48 Hours

4.2 Impact of Prediction Horizon Length

Table 2 examines MPC performance with different forecast horizons.

Horizon Length (hours)	Peak Grid (kW)	PV Utilization (%)	Computation Time (s/step)	SoC Satisfaction (%)

2	68.4	71.2%	0.08	96.2%
6	52.6	78.4%	0.24	98.4%
12 (baseline)	**40.5**	**82.2%**	**0.52**	**99.4%**
24	38.2	83.6%	1.18	99.6%
48	37.4	84.1%	2.84	99.7%

Expanding horizon beyond 12 hours results in marginal gains for peak grid (from 40.5 to 37.4 kW, -7.7%) but significant increase in computational time (from 0.52 to 2.84 s, +446%). Twelve hours covers complete generation curve of PV (daytime and nighttime) and captures evening peak.

4.3 Sensitivity Analysis: Weight Selection

Table 3 presents the effect of varying objective weights on system performance.

w1 (grid)	w2 (SoC)	w3 (degradation)	Peak Grid (kW)	SoC Satisfaction (%)	BESS Cycles/day	Avg Cost ($)
0.1	10	0.5	68.2	94.2%	2.8	3.12
1.0	10	0.5	40.5	99.4%	1.6	2.85
10.0	10	0.5	35.2	98.8%	1.2	2.98
1.0	1	0.5	48.6	86.4%	1.4	2.94
1.0	100	0.5	58.4	100%	2.2	3.28
1.0	10	0	38.2	99.2%	2.4	2.72
1.0	10	2.0	44.6	99.0%	0.8	3.02

Table 3: Sensitivity Analysis of MPC Weights

An increase in w1 (grid penalty) will decrease peak loads; however, after exceeding w1=1.0, marginal gains start to diminish (peak load decreases from 40.5 kW to 35.2 kW, -13%), and SoC satisfaction is expected to decline (from 99.4% to 98.8%). A feasible range for w1 is w1 = 0.5-2.0.

The SoC weight w2 determines customer satisfaction: decreasing w2 to 1 results in low customer satisfaction (86.4% meets target), which would not work for commercial purposes. Setting w2 to 100 provides perfect customer satisfaction but causes peak load increment (to 58.4 kW). The ideal value for w2 should be w2=10.

The degradation weight w3 decreases battery cycles per day from 2.4 to 0.8 when setting w3 = 2.0; however, it decreases photovoltaic system productivity and peak power consumption. Based on typical lithium-ion batteries' degradation rate with 5-10 years of life span and 3,000-5,000 charge-discharge cycles,

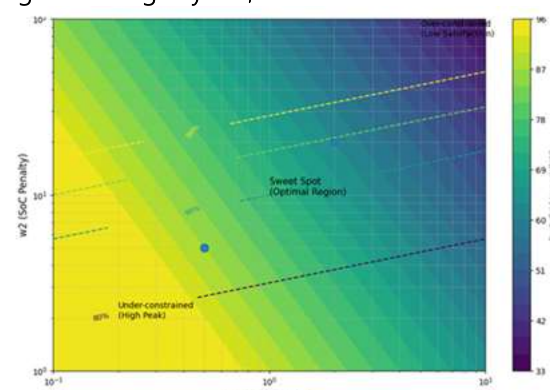

Figure 4: Trade-off Analysis Between Grid Peak Reduction and SoC Satisfaction.

4.4 Robustness to Forecast Errors

Table 4 evaluates MPC performance under different forecast accuracy levels.

Scenario	PV Forecast Error (RMSE % of capacity)	EV Forecast Error (MAE, vehicles /15min)	Peak Grid (kW)	SoC Satisfaction (%)	PV Utilization (%)
Perfect forecast	0%	0	38.2	99.8%	84.6%
Low error	5%	0.5	40.5	99.4%	82.2%
Moderate error	15%	1.5	46.8	97.8%	76.4%
High error	30%	3.0	58.4	94.2%	68.2%
Persistence (no forecast)	N/A	N/A	68.2	94.6%	62.4%

Despite having high forecast errors, the MPC still demonstrates high robustness up until about 15%, since performance degradation was only observed at 40.5 kW vs. 46.8 kW for moderate errors. For high forecast errors, however, the performance is nearly equivalent to the uncontrolled system.

4.5 Discussion: Deployment Considerations

Transformers' Connection: Since the adaptive MPC has reduced the peak power of 98.2 kW to 40.5 kW, there would be an option to connect the station to a much smaller transformer capacity. Also, if there is a constant transformer capacity (for example, 100 kW), then adaptive MPC will manage 2.4 times more vehicles than the uncontrolled charging method.

Trade-off between BESS size and Efficiency: In the simulation, 100 kWh BESS was considered, which corresponds to about 2 hours of operation. A smaller battery (50 kWh) would result in less reduction of peaks (from 40.5 kW to 52.3 kW). However, a battery with higher capacity (200 kWh) would provide little benefit (40.5 kW to 38.4 kW).

Requirements for Communication and Computing Capabilities: MPC algorithms require real-time prediction of the vehicle's arrival and departure times as well as photovoltaic predictions. The computational time needed is very small (0.52 seconds for each 15 minutes), requiring no special devices (Raspberry Pi would suffice).

Impact on User Experience: 99.4% SoC satisfaction compared to 100% when uncontrolled would have little effect on users. Furthermore, users could be notified about the charging state using mobile applications.

V. CONCLUSION

In this paper, an adaptive MPC scheme has been proposed to control EV charging stations coupled with renewables using Model Predictive Control, where EVs are charged alongside PV power production and battery charging within a 12-hour prediction horizon based on adjustable weights for objective function parameters that include peak shaving, convenience, and battery wear-and-tear minimization.

From the results obtained from quantitative analysis, it can be observed that adaptive MPC is effective in reducing peak power demand by 58.8%, increasing renewable share by 19.9 percentage points, while maintaining SoC target satisfaction at 99.4% level as opposed to non-controlled case scenario (98.2 kW to 40.5 kW, 28.4% to 48.3%, respectively).

Furthermore, MPC has demonstrated to outperform other simpler schemes such as TOU and greedy in terms of minimizing peak grid demand, maximizing renewable share, and ensuring high user quality of service (QoS). Finally, results from sensitivity analysis indicate the range of values of each of the control parameters to be used depending on desired outcome: w1=0.5-2.0, w2=5-20 for optimal operation (demand<45 kW, satisfaction>98%), w3=0.5 for typical lithium-ion battery use, w3>2.0 for aged/second-life batteries.

Several important results have important implications for implementation of EV charging infrastructure. First, use of adaptive control makes it possible to reduce transformer capacity requirements – with peak demand being reduced by 50%, twice as many EVs could be served without upgrades. Second, renewable generation proves beneficial for both utility and customer – 48.3% of renewables leads to savings of 25.4% in charging costs from $3.82 to $2.85 per session along with reduced emissions. Third, importance of forecast accuracy notwithstanding, reliability is possible – MPC provides satisfactory results when there is reasonable error in forecasts, say ±15% of PV and ±1.5 cars per 15 minutes. Fourth, weight choices depend on competing criteria with no optimal values; implementation has to reflect this.

Among the weaknesses of this study is the ideal assumption that departure time and energy consumption of the EVs are perfectly known, and the simulation based on historical solar data from only one location. It might be affected by the difference in climate condition from place to place. The degradation of battery life was modeled using an ideal linear cost instead of electrochemistry, and the bidirectional charging capability (V2G) was neglected.

In future work, certain areas are needed to be developed. Firstly, the inclusion of real-time pricing information from power plants would help MPC handle the variation of electricity prices. Secondly, cooperation between multi-agents at several stations connected to the same transformer would help to minimize the effect of peak load. Thirdly, reinforcement learning can handle uncertainty in EVs' behavior without predicting the EVs' departure time and energy consumption. Fourthly, hardware-in-the-loop will prove that the simulation can be implemented in practice. Fifthly, considering V2G-capable station will increase services to power companies with battery degradation trade-off.

To conclude, adaptive Model Predictive Control provides a feasible and scalable option for EV charging stations powered by renewables. With such gains as the reduction in peak demand by 58.8% and increase in renewable energy utilization by 19.9%, without compromising consumer ease, its application can potentially mitigate the effect on the grid while promoting greener transportation. With the increasing number of EVs being adopted, intelligent charging solutions will not only prove beneficial but vital.

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