

Article

Carbon-Aware Rolling-Horizon Energy Management of Electric Vehicles via Virtual Power Plants Under Carbon–Grid Conflict

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Abstract

The large-scale integration of electric vehicles (EVs) introduces significant operational challenges for power systems, particularly when grid-favourable operating periods coincide with high marginal carbon emissions. This paper proposes a carbon-aware rolling-horizon energy management framework for EV fleets coordinated through virtual power plants (VPPs), explicitly addressing such carbon–grid conflict conditions. The proposed framework prioritises grid-friendly scheduling through power and ramp constraints while enforcing energy-service equivalence and a policy-level carbon budget consistent with carbon peak and carbon neutrality objectives. Carbon awareness is incorporated as a secondary steering term within the rolling-horizon optimisation, enabling temporal shifting of EV charging toward low-carbon periods without compromising grid stability. A Pareto-based trade-off analysis is conducted to characterise the relationship between grid stress mitigation and carbon reduction, and a knee point is identified to select a balanced operating regime. Simulation results using real EV charging demand combined with a conflict-driven carbon intensity signal demonstrate that grid-oriented scheduling alone can increase emissions under carbon–grid mismatch. In the evaluated conflict scenario, the proposed carbon-aware rolling-horizon strategy achieves a 17.35% reduction in total CO₂ emissions relative to RH-NoCarbon scheduling while maintaining peak–valley load variation below 11.03 kW compared with 43.65 kW under uncontrolled charging. These results confirm that explicit carbon-aware coordination can significantly mitigate emissions without compromising grid operational stability. All control strategies are evaluated in a simulation environment using real EV charging demand data as exogenous inputs, ensuring realistic demand representation while enabling controlled assessment of operational performance. These findings highlight the necessity of embedding carbon considerations directly into operational EV scheduling and establish VPP-based rolling-horizon coordination as a practical mechanism for low-carbon power system operation.



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conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.**Keywords:** electric vehicles; virtual power plants; rolling-horizon optimisation; carbon-aware scheduling; Pareto trade-off; low-carbon power systems

1. Introduction

Transportation via electric vehicles (EVs) is becoming an important part of reducing our reliance on fossil fuels and reaching our goal of carbon neutrality. Research has shown

that 31% of China's cities have reached the "peak" in terms of their carbon output [1]. Therefore, the electricity sector must develop low-carbon strategies in order to assist with reaching the target of carbon neutrality. However, there are many operational challenges associated with large numbers of EVs being integrated into the power grid, especially during times when the uncoordinated charging of these vehicles causes high levels of demand on the distribution network [2]. The level of carbon savings from using an EV depends greatly upon when and how the vehicle is charged in relation to the carbon intensity of the electricity supply in the area in which the vehicle is being charged [3]. For example, researchers used data from the WECC and found that if one uses average emission factors for EV charging, then over 1.5 million EVs will be charged at a higher emission rate than the electricity supplied to them before charging. The above demonstrates the need for marginal carbon intensity signals in order to optimise EV charging [3]. Other researchers have also studied the effect of different grid emission allocation methodologies on EV greenhouse gas benefits by analysing the differences between average vs. marginal emission accounting for different charging scheduling strategies. The methodology used to allocate emissions poses a major influence on both modelled emissions and policy recommendations based on those emissions [4]. This study focuses on operational scheduling evaluation using real-world EV charging demand data within a simulation-based rolling-horizon optimisation framework to analyse carbon-grid trade-offs under controlled conditions.

1.1. Related Work

Virtual power plants (VPPs) have emerged as an effective coordination mechanism for managing aggregated EV charging loads while providing grid services. A multidisciplinary overview of EVs role in grid stability, vehicle-to-grid (V2G) technology, demand response and VPP aggregation for EV integrations in the power grid is provided [5]. The VPP framework provided a centralised optimisation of distributed grid resources and converted EVs into an active grid asset to provide ancillary services. Recent implementation studies demonstrate the viability of VPP-based EV coordination using real-world operational data [6]. The authors of [7] explored the potential of EV charging flexibility when employed in conjunction with demand response and V2G technologies to provide benefits to the power system. These studies highlighted the quantitative benefits of VPP in grid stress reduction and renewable energy integration.

Multi-objective optimisation and Pareto analysis are inherently involved in EV coordination due to trade-offs between conflicting objectives such as grid operational requirements, economic cost, and environmental impacts. An EV-based microgrid scheduling framework is proposed in [8] that utilised particle swarm optimisation to generate Pareto sets for trade-offs between operational objectives using real-world smart grid data. The authors of [9] developed well-distributed Pareto-optimal solutions across multiple optimisation objectives, including load variance, voltage stability and energy costs. The study highlights that the insights of Pareto-based approaches are superior to single or weighted-sum formulations to make well-informed decisions. The authors of [10] further explored this approach in EV management from a complex systems viewpoint, coordinating planning elements of EVs across both transportation and power sectors.

In the optimisation framework, model predictive control (MPC) becomes another dominant paradigm for real-time EV charging coordination due to its ability to predict, handle constraints and adapt to uncertainty through receding-horizon implementations [11]. The author of [12] utilised a stochastic MPC framework for reserve provision from EV aggregates, explicitly modelling prediction uncertainty and aggregate dynamics. A simulation tool for V2G-enabled demand response based on MPC is proposed [13] that demonstrated revenue maximisation using MPC for EV aggregators using grid operational limits. The

inherent property of rolling horizon is assessed by the added value of bidirectional EV energy flow implemented in [14] using a mixed integer linear rolling-horizon optimisation model over 48 to 72 h prediction windows. This optimisation formulation adjusts charging schedules in response to evolving system conditions that manage computational tractability with operational effectiveness for large-scale fleet management.

Convex optimisation formulations provide global optimality and computationally tractable solutions that make it an attractive formulation for real-time EV energy management. A comprehensive energy management strategies review is conducted [15], which highlighted that convex optimisation approaches provide an efficient solution with polynomial-time complexity. The authors of [16] incorporated the machine learning component using an input convex neural network model for battery optimisation in power systems. A multi-objective dispatch framework for batteries and renewable generation using a weighting-based convex approach is proposed in [17]. Similarly, the authors of [18] formulated a lossy energy storage convex formulation that incorporates realistic efficiency losses while maintaining a tractable problem structure.

Carbon-aware energy management is studied using (a) marginal carbon intensity and temporal load shifting and (2) carbon budget constraints and policy compliance. The temporal variations in grid carbon intensity provide an opportunity for emission reduction through intelligent load shifting. This formulation introduced a conflicting phenomenon with low-carbon periods, termed carbon-grid conflict. The authors of [19] introduced smart charging of EVs to demonstrate that marginal emission factors differ substantially from average factors and must be counted in charging optimisation. The life cycle emissions and policy implementations of EVs in a carbon-intensive energy system are studied in [20], which demonstrated that net EV emissions are determined by the carbon intensity of electricity generation, seasonal variability, and charging behaviour. Furthermore, the study found that EVs provide a long-term mitigation potential when decarbonisation is actively pursued and increase emissions with short-term charging during high-carbon periods.

The second formulation for carbon-aware energy management incorporates carbon content into operational optimisation for EV charging with climate policy objectives. The authors of [21] formulated online optimisation with a long-term carbon constraint that met the critical requirements for carbon budget enforcement with cumulative constraint satisfaction over extended horizons. The formulation addressed sustainability-constrained control problems of carbon peak and carbon neutrality policies. The integration of renewable energy and power system decarbonisation further broadens the context of carbon-aware EV management optimisation formulation. A comprehensive review of renewable energy integration for climate resilience is presented in [22]. The review discussed pathways to decarbonise the energy system and mitigate climate impact through coordinated resource management. Similarly, the authors of [23] analysed the challenges and opportunities of decarbonisation goals using renewables integrations; coordinated optimisation using generation; and storage and flexible demand resources, including EVs.

Grid integration and demand response provide decarbonisation goals using (a) aggregated-based flexibility services from distributed resources and (b) coordinated charging algorithms and grid impact. The authors of [24] employed aggregated-based flexibility using data-driven tools for aggregated coordinated heterogeneous flexible loads, including EVs. The proposed work provided system-level services while satisfying the individual resource constraints for flexibility. Contrarily, the coordinated charging algorithms were designed in [2] to reduce the power grid impact using EV charging. The authors of [25] considered distributed photovoltaic, grid and EV transactions for an optimal planning method for EV charging stations. A comprehensive taxonomy of solution approaches and the identification of research gaps of optimisation techniques in EV charging scheduling, routing, and spatio-temporal demand

coordination was reviewed [26]. In addition, multi-objective optimisation was analysed using a Pareto-based trade-off; however, in EV scheduling, limited studies integrate Pareto analysis for multi-objective formulation. The Pareto-based trade-off becomes an effective tool within carbon-constrained rolling-horizon frameworks to systematically quantify the trade-off between grid stress and cumulative emissions.

Despite substantial progress in EV coordination, there are three main limitations that remain evident from the existing literature. First, carbon–grid conflict conditions are optimised independently, i.e., either the grid performance or carbon emissions are optimised. Second, many of these formulations use weighted sum objectives to optimise multiple competing objectives without explicitly enforcing a hard carbon budget to ensure that the resultant optimised solution will result in a reduction in emissions that aligns with the desired policy. Third, few studies have investigated the trade-offs between peak–valley smoothing and cumulative emissions through the application of convex rolling-horizon formulations. These gaps serve to establish the central research question for this study:

What are the optimal ways to coordinate the charging of EV with respect to carbon–grid conflict conditions while ensuring energy service equivalence, carbon budget compliance and computational tractability?

1.2. Research Gaps and Contributions

While previous research made significant advancements in carbon-aware scheduling optimisation, a few critical research gaps remain. Most of the previous studies formulated the grid stress mitigation and carbon reduction as separate problem formulations. There is a pressing need to formulate and resolve the carbon–grid conflict that arises when grid-favourable operating periods coincide with high marginal emissions. The proposed research addresses this issue by formulating a carbon-aware rolling-horizon energy management framework for EV coordination through VPP. The pertinent contributions of the proposed framework are as follows:

- Explicitly characterises carbon–grid conflict conditions through time-varying marginal carbon intensity signals, revealing limitations of grid-only EV coordination strategies.
- A rolling-horizon EV energy management formulation is developed for VPPs that explicitly embeds carbon policy compliance through an absolute carbon budget while preserving grid-friendly operation.
- A systematic Pareto frontier is constructed to characterise the trade-off between peak–valley load smoothing and carbon emissions, with a knee-point selection methodology to identify balanced operating regimes.

The proposed integrated approach provides both operational guidelines for VPP operators and policy insights for regulatory frameworks supporting low-carbon power system operation.

1.3. Paper Organisation

The paper is organised as follows: Section 2 presents the system model and mathematical formulation for the optimisation problem. Section 3 proposes the carbon-aware rolling-horizon EV charging strategy and discusses the feasibility of the proposed optimisation formulation. Section 4 evaluates the performance of the proposed EV charging strategy. Section 5 concludes the paper and suggests future directions.

2. System Model and Mathematical Formulation

A power system with a large population of EVs coordinated through VPP is considered for the mathematical formulation. The VPP acts as an aggregation and decision-making layer between EV users and the power system operator. Furthermore, it provides charging schedules to mitigate grid stress while implementing carbon reduction policies. The

proposed framework operates at the operational scheduling level, rather than at the control or stability regulation level. As a result, the formulation emphasises feasibility, a continuous power trajectory, and compliance with policy instead of closed-loop control stability.

The system operates in discrete time, considering a scheduling horizon time discretised into uniform intervals indexed by $t \in \mathcal{T} := \{1, 2, \dots, T\}$, with sampling interval Δt (hours). Let $P(t)$ be the scheduled/controlled EV charging power (kW) dispatched by the VPP (decision variable), $P^{\text{uc}}(t)$ be the uncontrolled EV charging power (kW) inferred from station/fleet data profile, $\lambda(t)$ be the time-varying grid carbon intensity (kgCO_2/kWh), and E_{tot} be the total daily EV energy demand (kWh). To ensure fairness and service preservation, the total EV energy delivered under the VPP-controlled schedule must equal the baseline energy demand:

$$E_{\text{tot}} := \sum_{t=1}^T P^{\text{uc}}(t) \Delta t \quad (1)$$

The controller charging schedule must satisfy the energy constraint:

$$\sum_{t=1}^T P(t) \Delta t = E_{\text{tot}} \quad (2)$$

The constraint in (2) prevents artificial emission through load curtailment and ensures that all EV users are provided with an identical charging service. To mitigate the grid stress and maintain grid operation safety, the VPP enforces the grid operational constraints:

$$\text{Power capacity constraint } 0 \leq P(t) \leq \bar{P}, \forall t, \quad (3)$$

where the aggregate EV charging power varies from 0 to $\bar{P}$ that represents the maximum admissible aggregate EV charging power determined by transformer, feeder, or station limits;

$$\text{Ramp-Rate Constraint } |P(t) - P(t-1)| \leq R, \forall t \geq 2, \quad (4)$$

where the ramp rate is constrained to the maximum allowable ramp rate R , which reduces rapid power fluctuations, transformer thermal stress, and tidal current crossing.

In this study, a synthetic marginal carbon intensity is created as a realistic example of what would occur in high renewable energy penetration systems in terms of day-to-day variations in carbon emissions from generation. The carbon intensity for each hour was determined on a 15 min basis ($\Delta t = 0.25$ h). High carbon intensities ($\lambda_t \approx 0.95$ $\text{kg CO}_2/\text{kWh}$) were applied to the afternoon/evening peak demand periods (5 p.m.–9 p.m.), with low carbon intensities ($\lambda_t \approx 0.05$ $\text{kg CO}_2/\text{kWh}$) applied to the mid-day periods when solar dominates the grid. Moderate carbon intensities ($\lambda_t \approx 0.40$ $\text{kg CO}_2/\text{kWh}$) were applied to the early morning hours. The resulting synthetic marginal carbon intensity time series has small random Gaussian fluctuations ($\sigma \approx 0.03$) that were included to represent short-term changes in the hourly carbon intensity. This resulting time series is both deterministic and fully replicable.

The EV charging-related carbon emissions at time t are modelled as

$$e(t) = \lambda(t)P(t)\Delta t \quad (5)$$

The total carbon emissions over the scheduling horizon T are formulated as

$$E_{\text{tot}}^{\text{CO}_2} = \sum_{t=1}^T \lambda(t)P(t)\Delta t. \quad (6)$$

The total carbon emissions are constrained by an absolute carbon budget that is imposed to align with carbon peak and carbon neutrality objectives:

$$E_{\text{tot}}^{\text{CO}_2} \leq B. \quad (7)$$

The budget is formulated relative to the uncontrolled charging baseline as

$$B = \rho \sum_{t=1}^T \lambda(t) P^{\text{uc}}(t) \Delta t, \quad 0 < \rho < 1, \quad (8)$$

where ρ encodes the targeted emission reduction between 0 and 1; this constraint on carbon emission provides a hard policy guarantee that ensures that carbon-aware scheduling achieves measurable emission reductions.

To formulate the optimisation problem, the grid-oriented objective function is formulated to mitigate the grid stress to achieve smooth charging trajectories. The objective function is formulated as a quadratic deviation penalty of the power trajectory as

$$J_{\text{grid}} = \sum_{t=1}^T (P(t) - \bar{P}(t))^2, \quad (9)$$

where $\bar{P}(t)$ is a reference trajectory that is defined as the local moving average of the uncontrolled baseline charging profile over the prediction horizon, i.e., $\bar{P}(t) = \frac{1}{H} \sum_{h=0}^{H-1} P^{\text{uc}}(t+h)$.

The second optimisation objective is formulated as a carbon-aware term, namely,

$$J_{\text{carbon}} = \sum_{t=1}^T \lambda(t) P(t) \Delta t. \quad (10)$$

This objective function steers the temporal allocation of charging within the feasible set to avoid carbon-grid conflict.

The day-ahead VPP scheduling problem is formulated using the centralised energy management problem, namely,

$$\begin{aligned} \min_{P(1:T)} \quad & J_{\text{grid}} + \varepsilon_c J_{\text{carbon}} \\ \text{s.t.} \quad & (2)-(4), \\ & (7). \end{aligned} \quad (11)$$

In the multiple-objective formulation, the $\varepsilon_c \geq 0$ is a tunable carbon-weight coefficient to formulate as a weight sum objective. The weight ε_c variations yield a Pareto frontier between grid stress mitigation and carbon emission reduction.

3. Proposed Carbon-Aware Rolling-Horizon Energy Management

3.1. Motivation for Rolling-Horizon Scheduling

In optimisation formulation for carbon-aware scheduling, EV charging demand, carbon intensity and grid conditions are inherently stochastic and time varying. The solution of the optimisation problem in (11) assumes static, day-ahead scheduling that may lead to infeasible or suboptimal operation due to time-varying and stochastic variations. To address the limitations of the formulation in (11), the proposed framework adopts a rolling-horizon (receding window) scheduling strategy to encounter the effect of time-varying behaviour. The formal stochastic or probabilistic uncertainty quantification remains an important future work extension. The formulation updates the decision as new information becomes available, preserves feasibility under uncertainty and avoids complicated

theoretical stability assumptions. The system diagram of the proposed carbon-aware rolling-horizon scheduling is depicted in Figure 1.

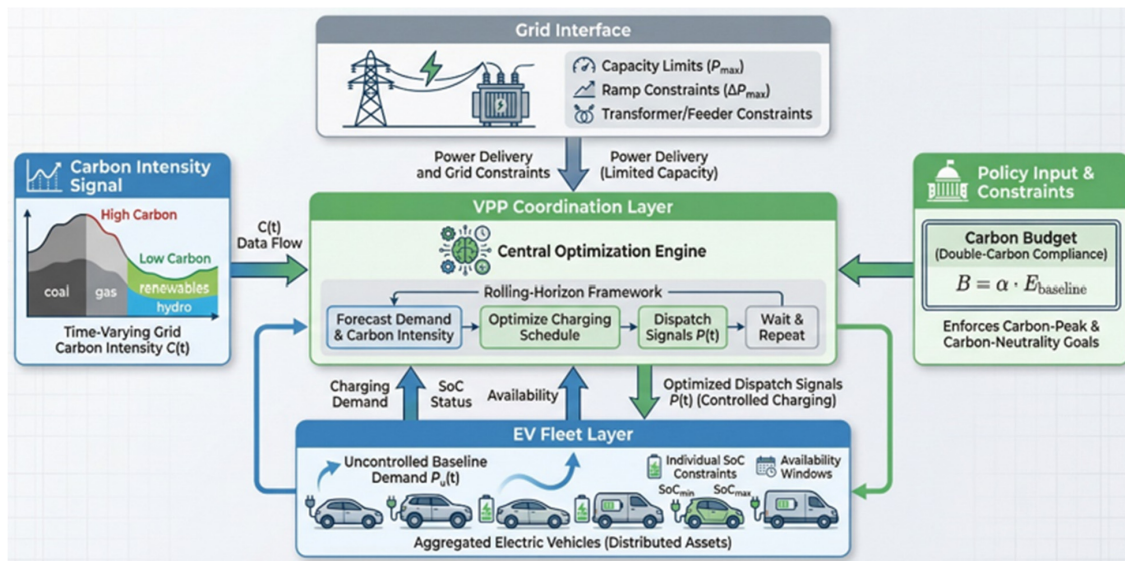


Figure 1. System diagram of carbon-aware EV charging Scheduling scheme using VPP. The new rolling-horizon optimisation approach differs from traditional day-ahead optimisation in two ways. It first enforces dynamic cumulative energy service equivalence and carbon budget compliance instead of only at the final time. Second, it combines grid smoothing with the carbon objective into one feasible constrained convex problem that maintains feasibility as the system state changes. Therefore, this new formulation allows for real-time re-allocation of charging energy based on the current carbon intensity while maintaining all other policy compliance and grid operating constraints.

3.2. Rolling-Horizon Problem Formulation

In the rolling-horizon problem formulation, instead of solving problems as a whole, at each time step k , the VPP solves a truncated optimisation problem over the prediction horizon $\mathcal{H}_k := \{k, k+1, \dots, k+H-1\}$. The same procedure repeats on the updated horizon at the next time step $k+1$.

Let $E_{del}(k)$ be defined as the cumulative energy delivered up to time $k-1$, while $C_{used}(k)$ is defined as the cumulative carbon emitted up to time $k-1$. The remaining energy and carbon allowances are formulated at time step k , as given by

$$E_{rem}(k) = E_{tot} - E_{del}(k), \quad B_{rem}(k) = B - C_{used}(k). \quad (12)$$

A soft horizon energy target is defined at time step k , as given by

$$E_{tar}(k) = \frac{E_{rem}(k)}{T - k + 1} \cdot H. \quad (13)$$

The rolling-horizon optimisation problem is formulated at time step k :

$$\begin{aligned} \min_{P(\tau), \tau \in \mathcal{H}_k} \quad & \sum_{\tau \in \mathcal{H}_k} (P(\tau) - \bar{P}_k(\tau))^2 \\ & + \varepsilon_E \left(\sum_{\tau \in \mathcal{H}_k} P(\tau) \Delta t - E_{tar}(k) \right)^2 \\ & + \varepsilon_C \sum_{\tau \in \mathcal{H}_k} \lambda(\tau) P(\tau) \Delta t \\ \text{s.t.} \quad & 0 \leq P(\tau) \leq \bar{P}, \\ & |P(\tau) - P(\tau-1)| \leq R, \\ & C_{used}(k) + \sum_{\tau \in \mathcal{H}_k} \lambda(\tau) P(\tau) \Delta t \leq B. \end{aligned} \quad (14)$$

The rolling-horizon optimisation problem formulation in (14) combines three interacting mechanisms: (i) hard constraints enforcing energy equivalence and carbon budget compliance, (ii) convex quadratic penalties promoting grid-smoothing behaviour, and (iii) a linear carbon-weighted steering term that redistributes charging within the feasible region. These interactions ensure that carbon reduction is not achieved through load curtailment or infeasible operation, but strictly through temporal redistribution of flexible demand. The convex structure guarantees computational tractability and global optimality at each horizon step.

After solving the optimisation problem (14), only the first-step decision $P(k)$ is implemented. The remaining energy is redistributed in the final steps to ensure exact satisfaction of (2). This optimisation formulation guarantees exact energy-service satisfaction, cumulative carbon budget compliance and smooth grid-friendly operation. The carbon-weight parameter ε_c is selected through a systematic sweep to generate a Pareto frontier between the peak valley, load variation and total emissions. A knee point is identified as the operating point that balances grid and carbon objectives using the optimisation formulation in (14). The carbon-aware rolling-horizon VPP scheduling algorithm is given below in Algorithm 1.

Algorithm 1: Carbon-Aware Rolling-Horizon Energy Management via VPP.

Inputs: Baseline EV charging profile $P^{\text{UC}}(1:T)$, carbon intensity signal $\lambda(1:T)$, sampling interval Δt , horizon length H , power limit $\bar{P}$, ramp limit R , carbon reduction ratio ρ and weighting parameters $\varepsilon_E, \varepsilon_c$.

Outputs: Controlled EV charging schedule $P(1:T)$

1. **Compute total energy requirement**

$$E_{\text{tot}} \leftarrow \sum_{t=1}^T P^{\text{uc}}(t) \Delta t.$$

2. **Compute carbon budget**

$$B \leftarrow \rho \sum_{t=1}^T \lambda(t) P^{\text{uc}}(t) \Delta t.$$

3. **Initialise**

$$E_{\text{del}} \leftarrow 0, C_{\text{used}} \leftarrow 0, P(0) \leftarrow P^{\text{uc}}(1).$$

4. **For** $k = 1$ **to** $T - H$ **do**

a. **Compute remaining energy**

$$E_{\text{rem}} \leftarrow E_{\text{tot}} - E_{\text{del}}.$$

b. **Set horizon energy target**

$$E_{\text{tar}} \leftarrow \frac{E_{\text{rem}}}{T-k+1} \cdot H.$$

c. **Solve the rolling-horizon problem** (RH- k) over $\mathcal{H}_k$

d. **Apply first-step decision** $P(k)$

e. **Update:**

$$E_{\text{del}} \leftarrow E_{\text{del}} + P(k) \Delta t, C_{\text{used}} \leftarrow C_{\text{used}} + \lambda(k) P(k) \Delta t.$$

5. **Terminal energy completion**

Assign the remaining energy while satisfying power and ramp constraints over the last H steps to solve a terminal constrained optimisation:

$$\begin{aligned} \min_{\{P(\tau)\}_{\tau=T-H+1}^T} \quad & \sum_{\tau=T-H+1}^T (P(\tau) - P_{\text{ref}}(\tau))^2 \\ \text{s.t.} \quad & \sum_{\tau=T-H+1}^T P(\tau) \Delta t = E_{\text{rem}}(T-H+1), \\ & 0 \leq P(\tau) \leq \bar{P}, \\ & |P(T-H+1) - P(T-H)| \leq R, \\ & |P(\tau) - P(\tau-1)| \leq R, \tau = T-H+2, \dots, T, \\ & C_{\text{used}}(T-H+1) + \sum_{\tau=T-H+1}^T \lambda(\tau) P(\tau) \Delta t \leq B. \end{aligned}$$

Then assign the terminal schedule :

$$P(T-H+1:T) \leftarrow \{P(\tau)\}_{\tau=T-H+1}^T.$$

Return $P(1:T)$

3.3. Theoretical Guarantees of Rolling-Horizon Formulations

The theoretical guarantees focus on feasibility, policy compliance, and grid-friendly behaviour, which are appropriate for scheduling-level problems.

Proposition 1 (Convexity and Existence). *At each rolling-horizon time step k , the optimisation problem in (14) is a convex quadratic program. If the feasible set is nonempty, an optimal solution exists.*

Proof. The objective functions in optimisation problem (14) are formulated as a weighted sum of a convex quadratic and linear terms. The constraints of the optimisation formulation are all affine, hence the problem formulation is a convex optimisation, and with the existence of a feasible set, it is convex and closed. This ensures both the convexity and solution existence of the optimisation formulation in (14). $\square$

Proposition 2 (Energy Equivalence). *If the rolling-horizon algorithm enforces the terminal energy completion step, the total energy delivered by the VPP-controlled schedule satisfies*

$$\sum_{t=1}^T P(t)\Delta t = E_{\text{tot}}.$$

Interpretation: To satisfy the total energy delivered, this guarantees that carbon and grid benefits are not achieved by curtailing EV charging demand. This ensures that all strategies deliver the same total EV energy, which is compared with the uncontrolled baseline algorithm.

Proposition 3 (Carbon Budget Satisfaction). *If the rolling-horizon constraint*

$$C_{\text{used}}(k) + \sum_{\tau \in \mathcal{H}_k} \lambda(\tau)P(\tau)\Delta t \leq B$$

is enforced at every time step k , then the cumulative emissions over the full horizon satisfy

$$\sum_{t=1}^T \lambda(t)P(t)\Delta t \leq B.$$

Interpretation: This provides a hard policy guarantee: the proposed framework ensures compliance with carbon-peak or carbon-cap targets at the operational level.

Proposition 4 (Bounded and Smooth Charging). *The scheduled EV charging trajectory satisfies*

$$0 \leq P(t) \leq \bar{P}, \quad |P(t) - P(t-1)| \leq R, \quad \forall t,$$

ensuring bounded power injection and limited inter-temporal variation.

Interpretation: These constraints act as practical proxies for grid stability, mitigating transformer overload risk, excessive current ramps, and operational stress.

Remark on Stability

The proposed framework guarantees operational stability through propositions 1, 2, 3 and 4 using the boundedness, smoothness and feasibility properties for energy scheduling and EV coordination. The framework does not claim a closed-loop MPC sense or Lyapunov stability.

3.4. Design Insights and Operational Interpretation

The proposed framework can be embedded as a policy-constrained convex receding-horizon control layer operating at the scheduling layer for power management. Unlike traditional weighted-sum multi-objective optimisation approaches, the proposed formulation enforces a dual structure (objective steering + tight budget), ensuring both flexibility and guaranteed compliance. The formulation utilises a rolling-horizon mechanism that enables adaptive reallocation of charging power while preserving feasibility at each time step. This formulation provides an optimal resolution of carbon-grid conflict conditions using redistribution of EV charging toward a lower-carbon period within the ramp and capacity limits.

4. Simulation Studies and Results

This section presents the performance evaluation of the proposed carbon-aware rolling-horizon energy management framework through a comprehensive simulation study. We had three main objectives: assess the grid stress mitigation, quantify the impact on carbon emission under carbon-grid conflict, and characterise the trade-off between the grid performance and carbon reductions. All of the simulations were conducted using our proposed rolling-horizon formulation with both energy equivalence and ramp constraints to ensure that the performance of each of the studied strategies can be compared fairly. The present study assumed perfect knowledge of the carbon intensity signal within the rolling horizon and does not explicitly model forecast error or lag correction. Incorporating forecast uncertainty represents future work.

4.1. Simulation Setup and Scenarios

The simulation studies utilised real-world charging demand for EVs provided from publicly available datasets of charging stations [27]. The future high demand of EVs in dense urban fleet aggregation was demonstrated by the scaling of baseline demand by a factor of 50. This scaling emulated a large-scale electrification of transportation in metropolitan areas where a large fleet of thousands of EVs may be simultaneously coordinated for an aggregator. The temporal structure of the EV demand remained intact, while the magnitude was scaled to represent aggregated fleet behaviour. The length of the scheduling window was 24 h, divided into intervals of 15 min ($T = 96$, $\Delta t = 0.25$ h). The total amount of energy required by the EVs was fixed and equal for all the studied strategies, thereby allowing for emission reductions solely through the temporal repositioning of the energy use and not through any curtailment of the demand. The simulation of the RH-Carbon optimisation problem was formulated as a convex quadratic program and implemented in Python (version 3.13.1) using the CVXPY optimisation framework. The optimisation problem was solved using the OSQP solver with absolute and relative tolerances set to 10^{-6} and a maximum iteration limit of 20,000. As the optimisation formulation was convex, it guaranteed global optimality.

To determine whether the proposed approach is necessary to address the issue of carbon-grid conflict, we established a carbon-grid conflict scenario. This scenario was established as follows: The grid's favourable periods of the day (evening hours when the aggregate demand is typically smooth) corresponded to periods with the highest marginal carbon intensity (fossil fuel-dominated generation). The low-carbon periods (midday solar surplus) occurred at times when the incentives to charge the battery would have been oriented toward meeting grid needs. The conflict scenario was intentionally designed to simulate smoothing periods coinciding with elevated marginal emissions. This setup reflects conditions expected in systems with high renewable penetration and motivates the need for explicit carbon awareness in operational scheduling. The temporal overlapping

between grid-favourable smoothing intervals and high marginal carbon intensity periods was evaluated. In the simulation scenarios, approximately 5 h out of 24 h (around 20.8% of the horizon) corresponds to a grid-smoothing incentive overlap with the carbon intensity period, i.e., $\lambda_t \approx 0.95$ kg CO₂/kWh. The proposed RH-Carbon strategy mitigates the conflict and reduces total emissions of 38.36 kg and achieves a 17.35% reduction relative to RH-NoCarbon. This quantitative analysis reflects a measurable operational impact of carbon–grid conflict. Moreover, the generated EVs profile reflects plausible future operating conditions in a modern power grid scenario. The following charging strategies are evaluated for analysis:

Uncontrolled charging (UC): EVs charges according to baseline demand without coordination.

Rolling horizon without carbon (RH-NoCarbon): Rolling-horizon scheduling is implemented that minimises grid stress without carbon awareness.

Proposed rolling horizon with carbon aware (RH-Carbon): Proposed rolling-horizon scheduling with an explicit carbon budget and carbon-aware objective term. The simulation study operates at an aggregated fleet level and does not explicitly model individual driver behaviour (e.g., stochastic departure times, route choice, or real-time charging decisions). The driver's behaviour patterns are inherently reflected in real-world charging demand datasets. The proposed framework treats demand as an exogenous aggregate input in the optimisation formulation.

4.2. Grid Stress Mitigation Performance

The EV charging profiles under the three strategies are illustrated in Figure 2. The UC charging strategy exhibits high spike behaviour due to uncoordinated charging that leads to large peak variations. Quantitatively, the peak load of UC is 43.65 kW in comparison with RH-NoCarbon with 8.89 kW and RH-Carbon with 11.02 kW. Both rolling-horizon charging strategies reduce the load variations for grid stress mitigation. The proposed RH-Carbon exhibits a slightly higher peak value, reflecting the trade-off to avoid high-carbon charging periods.

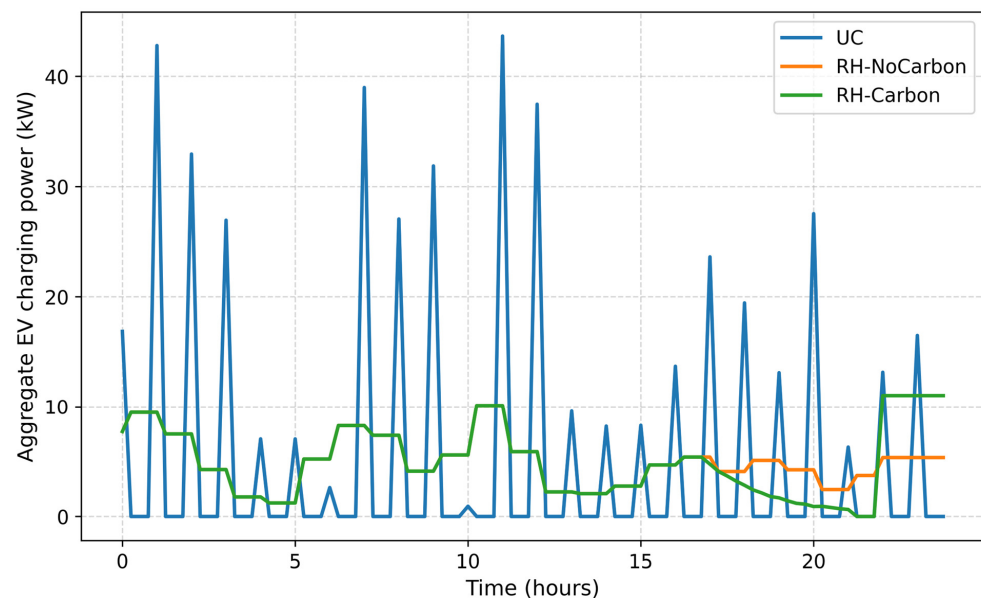


Figure 2. EV charging profiles under the UC, RH-NoCarbon and RH-Carbon strategies.

Cumulative CO₂ emissions over the scheduling horizon are depicted in Figure 3. The total emissions of UC is 45.24 kg, Rh-NoCarbon is 46.41 kg, and RH-Carbon is 38.36 kg. The two key observations from Figure 3 are as follows: Grid-only rolling-horizon scheduling can increase emissions. RH-NoCarbon shifts EV toward grid-favourable evening hours,

which coincide with high carbon intensity. In contrast, RH-Carbon scheduling avoids high-emission periods and achieves a 17.3% reduction relative to the RH-NoCarbon strategy.

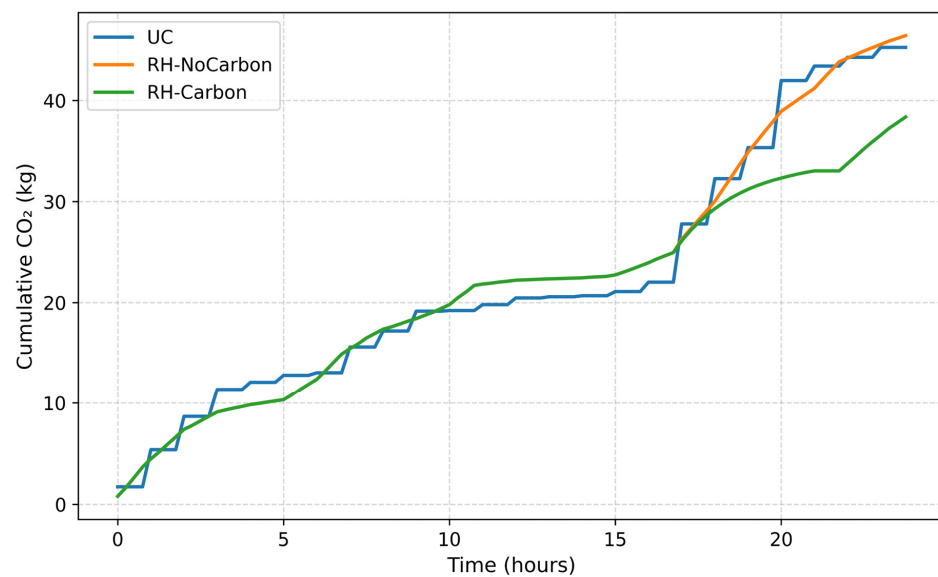


Figure 3. Three-strategy comparison of cumulative CO₂ emissions over the scheduling horizon.

The Pareto trade-off between grid smoothness and carbon reduction is presented in Figure 4. This plot is obtained by sweeping the carbon-weighting coefficient in the rolling-horizon objective. This Pareto analysis provides a structured multi-objective performance evaluation rather than relying on a single arbitrarily selected weighting parameter. The Pareto frontier demonstrates the flexibility in the trade-off between peak value and total CO₂ emissions reductions. Each point on the Pareto frontier represents a feasible operating schedule that satisfies all grid constraints. As the carbon weight increases, CO₂ emissions decrease monotonically, and the peak load variation increases gradually. This also verified the fundamental trade-off between grid smoothness and carbon reduction under conflict conditions. A knee point on the Pareto frontier was identified using a distance to ideal criteria between the trade-off between carbon reduction and grid smoothness. This operating point was adopted as the proposed operating region that provides a balanced compromise between grid stress and carbon reduction compliance.

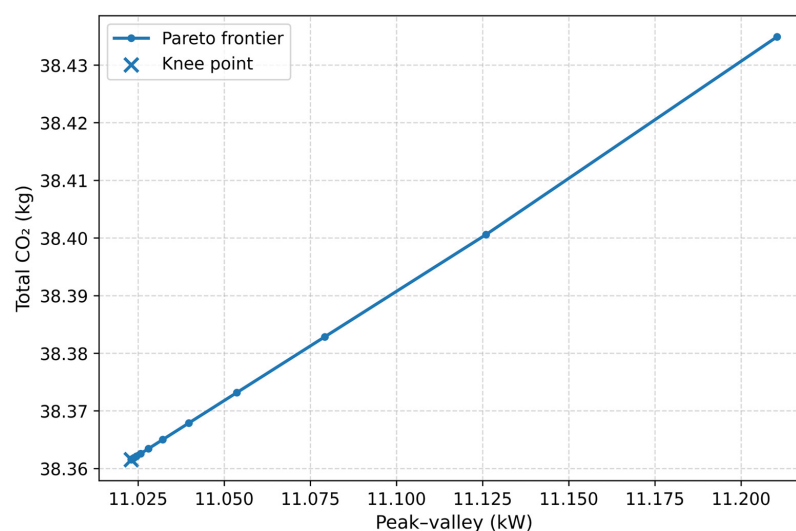


Figure 4. Pareto frontier between peak-valley load variation and total CO₂ emissions, obtained by sweeping the carbon-weighting coefficient in the rolling-horizon objective.

4.3. Charging Behaviour Interpretation

The EV charging behaviour of rolling-horizon strategies is illustrated in Figure 2. The carbon-aware scheduling reshapes EV charging in comparison with the RH-NoCarbon strategy. The proposed strategy reduces charging during high-carbon evening periods, reallocates energy toward lower-carbon intervals and maintains smooth power trajectories through ramp containment. The period of reduced charging does not result in service degradation; instead, it reflects the optimal deferral of flexible demand within the rolling-horizon framework. In the RH-Carbon formulation, energy equivalence conditions ensure that all EV energy requirements are fully satisfied by the end of the horizon.

4.4. Critical Performance Analysis

The critical performance results of UC, RH-NoCarbon, and RH-Carbon under carbon-grid conflict scenarios are given in Table 1. All three strategies deliver the same total EV energy (118.844 kWh), and their performance differences in grid and carbon reduction are due to the temporal reallocation of charging demand rather than energy curtailment.

Table 1. Core performance metrics analysis of three strategies.

Method	Total Energy (kWh)	Peak–Valley (kW)	Std Dev (kW)	Total CO ₂ (kg)	CO ₂ Reduction vs. UC (%)	CO ₂ Reduction vs. RH-NoCarbon (%)
UC	118.844	43.646	10.712	45.244	0.000	2.517
RH-NoCarbon	118.844	8.888	2.310	46.412	−2.582	0.000
RH-Carbon	118.844	11.023	3.255	38.362	15.212	17.346

When grid stress mitigation is compared with UC charging, both RH-NoCarbon and RH-Carbon strategies significantly reduce the peak load variation and standard deviation. UC exhibits a peak valley of 43.646 kW, reflecting highly coordinated charging behaviour. RH-NoCarbon reduces this value to 8.888 kW, demonstrating the effective grid stress mitigation, whereas RH-Carbon achieves a peak value of 11.023 kW, which is substantially lower than UC and only a modest increase relative to RH-NoCarbon. The RH-NoCarbon performance is better than the RH-Carbon strategy because grid-favourable scheduling coincides with high-carbon periods in the considered scenarios.

The carbon emission results reveal a critical insight where RH-NoCarbon produces 2.58% higher emissions than UC despite significantly improving the grid smoothness. This behaviour is due to grid-oriented scheduling that shifts EV charging toward grid-favourable evening periods, which in the simulation scenarios coincide with a high marginal carbon intensity. In contrast, the RH-Carbon strategy reduces the total emissions by 15.21% relative to UC and 17.35% relative to the RH-NoCarbon strategy. The RH-Carbon strategy explicitly steers EV charging away from high-carbon intervals and satisfies the grid constraints. The results in Table 1 demonstrate that grid-oriented scheduling alone may increase emissions under carbon-grid conflict, and that explicit carbon awareness is necessary to ensure emission reduction in such conditions.

4.5. Sensitivity Analysis with EV Penetration

The sensitivity analysis of EVS penetration is summarised in Table 2. The robustness of the proposed algorithm is evaluated by scaling baseline charging demand by a scaling factor of $\times 10$, $\times 25$, and $\times 50$. These scaling levels are used to represent different levels of EV integrations as moderate, intermediate and high EV aggregation simulation scenarios, respectively.

Table 2. Sensitivity analysis with respect to EV penetration scaling.

Scaling Factor	Method	Peak–Valley (kW)	Total CO ₂ (kg)	CO ₂ Reduction vs. RH-NoCarbon (%)
×10	RH-NoCarbon	1.778	9.282	-
	RH-Carbon	2.205	7.672	17.346
×25	RH-NoCarbon	4.444	23.206	-
	RH-Carbon	5.512	19.181	17.346
×50	RH-NoCarbon	8.888	46.412	-
	RH-Carbon	11.023	38.362	17.346
×50 Evening-Peak (Workplace)	RH-NoCarbon	29.257	92.890	-
	RH-Carbon	28.461	78.070	15.954

Table 2 demonstrates that both peak–valley variation and total emissions scale approximately proportionally with the EV penetration level. However, the relative emission reduction of the RH-Carbon method with respect to RH-NoCarbon remains constant at 17.346% across all scaling levels of EV penetration. This indicates that the proposed RH-Carbon method performance is invariant and remains valid for moderate and high EV adoption scenarios. In addition to the baseline real-world demand profile, we constructed an Evening-Peak (Residential) profile. This scenario reflects generality beyond a single demand trace for performance evaluation. The results show again that the RH-Carbon strategy reduces emissions up to 15.954% in comparison with the RH-NoCarbon method. The tabular analysis in Table 2 highlights the supervisor performance of the proposed method, specifically in carbon–grid conflict scenarios.

As compared with other EV coordination research studies, which are mainly focused on grid-oriented smoothing or cost minimisation [2,7,8], reported emissions reductions are generally indirect and based on a number of different scenarios, as well as limited explicit enforcement of carbon policy requirements. In comparison, the carbon-aware rolling-horizon framework discussed above is able to achieve an emissions reduction of 17.35% over that achieved by using a grid-oriented approach for scheduling under explicitly defined carbon–grid conflict conditions, and in addition provides guaranteed adherence to the total carbon budget. The methodology employed in this study also differs from the weighted-sum multi-objective methods often employed in previous studies, in that it includes hard carbon constraints within a convex, receding-horizon structure. This allows for both guaranteed adherence to carbon policies related to emissions levels and computational tractability.

In general, this framework has three benefits: (i) it guarantees that the carbon budget will be met at all times via cumulative constraint; (ii) it consistently produces emission reductions when the demand pattern involves conflicting demands from the carbon grid and the grid; (iii) it uses efficient computational techniques in that it solves convex quadratic programs in real time.

4.6. Robustness to Carbon-Intensity Profiles and Multi-Day Evaluation

For the robust analysis of the carbon intensity profile, we introduced a second profile with higher volatility and forecast uncertainty called Scenario B and used Scenario A as the baseline. Scenario B includes intra-day variability and a $\pm 10\%$ multiplicative forecast error applied to the carbon signal used by the controller, while emissions are evaluated using the true profile.

The analysis of both scenarios is summarised in Table 3 for emission reductions. In both scenarios, the RH-Carbon strategy reduces emissions and achieves 17.35%

(46.41 $\rightarrow$ 38.36 kg CO₂) reductions for Scenario A and 18.66% (28.14 $\rightarrow$ 22.88 kg CO₂) reductions for Scenario B relative to the RH-NoCarbon strategy. The results demonstrate the emission benefits of the proposed strategy under alternative profiles and forecasting uncertainty. This analysis was further extended to a multi-day evaluation to assess the temporal robustness for both Scenario A and Scenario B. The relative emission reduction by RH-Carbon remains consistent across days in Table 3, i.e., 17.35% for Scenario A and 18.66% for Scenario B. These analyses validate the stability of the proposed strategy behaviour over repeated daily operation.

Table 3. Robustness across carbon profiles (single-day results).

Carbon Profile	RH-NoCarbon CO ₂ (kg)	RH-Carbon CO ₂ (kg)	Reduction (%)	PV NoCarbon (kW)	PV Carbon (kW)
Scenario A (baseline conflict)	46.412	38.362	17.346	8.888	11.023
Scenario B (volatile + 10% forecast error)	28.135	22.884	18.662	8.888	15.740

4.7. Computational Performance and Scalability

The proposed rolling-horizon optimisation was formulated as a convex quadratic program and solved using the OSQP (via CVXPV) solver with the tolerances $\epsilon_{\text{abs}} = 10^{-6}$ and $\epsilon_{\text{rel}} = 10^{-6}$ and maximum iterations = 20,000. The computational performance was evaluated using the average solve time per rolling-horizon step and total run time, scaling with timestep T and horizon length H . Across all test cases, as shown in Figure 5 and Table 4, the average solve time per set ranges from 0.0117 s to 0.0235 s and shows a linear increasing trend with H for fixed T .

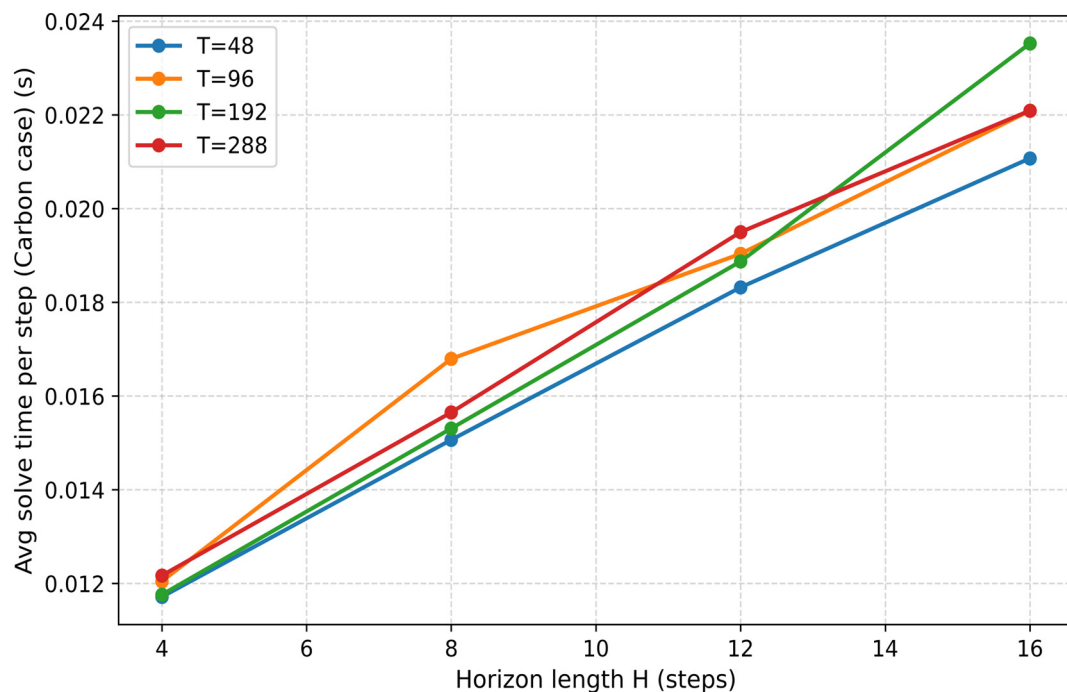


Figure 5. Average solve time per step vs. horizon length H for different T .

Table 4. Computational time analysis of the RH-Carbon strategy in seconds.

<i>T</i>	<i>H</i>	Avg Step Time (RH-Carbon) (Seconds)	Total Time (RH-Carbon) (Seconds)
96	4	0.0120	1.1200
96	8	0.0168	1.4943
96	16	0.0221	1.7889
192	8	0.0153	2.8314
288	8	0.0156	4.3969
288	16	0.0221	6.0303

The total solve time also shows a linear trend with increasing T since optimisation is solved repeatedly over T . The total run time remains below 6.3 s, even for the largest test case $T = 288$ and $H = 16$ (273 QPs; total 6.03 s). For the baseline day-ahead case $T = 96$ and $H = 8$, the total solve time was 1.49 s (89 QPs). These results indicate the computational feasibility of the proposed rolling-horizon strategy. During scalability, a small number of runs were reported infeasible for larger T and H , which can occur when the carbon budget becomes tight and strict ramp/terminal constraints. In the reported results in Figure 5 and Table 4, solutions were optimal across all steps.

5. Conclusions and Future Work

The study investigated the problem of large-scale EV integration in the power system to reduce carbon emissions. Specifically, this problem was evaluated under carbon-grid conflict by proposing a carbon-aware rolling-horizon energy management framework coordinated through a VPP. Unlike grid-oriented EV scheduling strategies, which are focused primarily on load-smoothing, the proposed framework has incorporated carbon considerations into operational decisions in addition to maintaining grid-friendly behaviour and energy service equivalence. When using realistic EV charging demand profiles with a conflict-driven carbon intensity signal, the results highlight that without carbon awareness, it can inadvertently cause an increase in emissions. Conversely, the proposed carbon-aware strategy was able to mitigate this effect and achieve a significant reduction in emissions with significantly lower peak–valley load variation than UC. The Pareto-based analysis also demonstrated a clear trade-off between grid smoothness and carbon reduction. Clearly, it showed the existence of a balanced operating regime where most of the emission benefits can be achieved with only a moderate increase in load variability. These results clearly demonstrate the need to include carbon signals into operational EV scheduling and establish VPP-based rolling-horizon coordination as a practical and policy-consistent method of facilitating low-carbon power system operation with massive EV penetration.

The proposed framework demonstrates strong performance in a simulation study; however, there are several practical challenges that must be considered for real-world deployment. The first challenge is related to forecasting marginal carbon intensity signals that are subject to uncertainty. This challenge can be addressed by incorporating a robust optimisation formulation that explicitly accounts for prediction uncertainties. The second challenge is related to inherent communication infrastructure issues, e.g., delays or packet losses that may introduce deviations between scheduled and realised charging power. The third challenge is that existing electricity markets and regulatory frameworks do not incorporate marginal carbon intensity signals into operational dispatch decisions. This implementation required policy and market reforms. Addressing these challenges enables practical adaptation of carbon-aware EV coordination strategies.

The proposed framework opens several structured research directions that can be quantitatively evaluated in future work: (1) Network-constrained AC power flow integration: Extend the current proxy-based grid constraints to a full AC power flow formulation. The performance can be evaluated using the voltage deviation (p.u.), the line congestion percentage, and reactive power support metrics under IEEE benchmark feeders over multi-day simulations. (2) Stochastic driver behaviour modelling: Incorporate probabilistic arrival/departure distributions and charging preferences using Monte Carlo simulation. Evaluation metrics may include expected emission reduction under uncertainty, variance in grid stress indicators, and service-level compliance probability. (3) Carbon forecast uncertainty quantification: Introduce stochastic or robust optimisation formulations to account for forecast errors in marginal carbon intensity. Future validation can quantify emission reduction degradation under controlled forecast error levels (e.g., $\pm 5\%$, $\pm 10\%$, $\pm 20\%$ prediction error). (4) Multi-day and seasonal validation: Extend the simulation horizon to seasonal datasets with varying renewable penetration. Key metrics include cumulative annual emission reduction (%), worst-case peak–valley variation, and computational scalability across extended horizons. (5) Real-time field deployment within VPP platforms: Implement the algorithm within an operational VPP testbed. Performance can be evaluated using real-time computational latency (ms per step), communication delay tolerance (seconds), and carbon budget compliance rate over pilot deployments.

These structured directions provide measurable evaluation pathways for extending the proposed carbon-aware rolling-horizon framework toward real-world implementation and validation.

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Nomenclature

Sets and Indices

t	Discrete time index
$\mathcal{T}$	Set of time indices
T	Total number of time intervals
H	Rolling-horizon length
P_t^{uc}	Uncontrolled baseline charging power

Parameters

Δt	Sampling interval (hours)
$P_{\max}$	Maximum admissible aggregate EV charging power (kW)
$R_{\max}$	Maximum allowable ramp rate (kW per interval)
E_{tot}	Total daily EV energy requirement (kWh)
λ_t	Time-varying marginal carbon intensity (kg CO ₂ /kWh)
γ	Target carbon reduction ratio
ϵ	Carbon-weight coefficient in objective function

Decision Variables

P_t Scheduled EV charging power at time t (kW)

Derived Quantities

E_t Cumulative delivered energy up to time t (kWh)

C_t Cumulative carbon emissions up to time t (kg CO₂)

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