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Probabilistic Evaluation of the Contribution of Smart EV Charging Strategies to Security of Supply

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Abstract—As climate change accelerates and the energy crisis deepens, electric vehicle adoption is growing rapidly with strong governmental support. However, this growth is straining electricity networks, prompting expensive infrastructure upgrades and a need for smart charging solutions, including Grid-to-Vehicle and Vehicle-to-Grid. This research synthesizes residential vehicle travel patterns from statistical data to model the electrical demand profile from uncoordinated charging, capturing the diversity in driving behaviour. It then develops scalable models for unidirectional and bidirectional smart charging to assess their impact on system reliability and their capacity credit within a probabilistic Monte Carlo framework. The case studies additionally present sensitivities on smart charging participation, electric vehicle uptake, and installed wind capacity. Results show that both smart charging concepts enhance reliability and that their capacity contributions grow with increased user engagement and wind generation, though the benefits plateau beyond certain thresholds.

Keywords—electric vehicles, Monte Carlo, reliability, smart charging, vehicle-to-grid.

I. INTRODUCTION

The growing adoption of electric vehicles (EVs), to help combat air pollution and decarbonise part of the transport sector, presents both challenges and opportunities for future power systems, particularly in relation to charging behaviours and their implications for system reliability and planning. To assess the potential impact of EVs on the network and inform future expansion planning, it is essential to accurately model EV travel and charging behaviours. Charging behaviour varies significantly depending on the context – residential, workplace, destination, or rapid charging – with residential charging predicted to account for 58–64% of total charging events by 2030 [1]. Accurate demand characterisation requires inputs including arrival and departure times, state of charge (SoC), battery capacity, and rated charging power [2].

Several studies have used travel survey data [3], [4], [5] or EV trials with GPS loggers [6], [7] to derive usage patterns, though sample sizes remain limited and may not reflect current trends. Alternatively, probability distributions have been used to model vehicle arrival-departure and travel distance [8], [9]. Assumptions around initial SoC at plug-in vary widely, with some studies underestimating it due to comparisons with traditional fuel vehicles behaviours [10] or conversions of daily mileage into charging demands [6], [2]. Based on the SwitchEV trial statistics, over 50% of EVs begin charging with more than 53% SoC [11].

Uncoordinated or uncontrolled charging assumes users plug in as soon as their journey ends, with 70% of EVs following this pattern [12], often charging at rated power until reaching 90–98% SoC [6], [11], though studies caution against charging to full capacity due to battery life concerns [13]. In contrast, unidirectional smart charging, known as Grid-to-Vehicle (G2V), enables dynamic charging control within user-defined constraints, using either centralised [2], [14] or decentralised strategies [15]. In research, objectives range from peak shaving [16], [17] and cost reduction [18], [19], to minimising power losses [20] and greenhouse gas emissions [21], [22]. The user experience is also sometimes considered [23].

Bidirectional smart charging, or Vehicle-to-Grid (V2G), extends these benefits by allowing EVs to discharge back to the grid, enhancing peak shaving potential [16] and supporting system flexibility. It introduces new constraints such as depth of discharge (DoD) to limit the effects of battery degradation [13], [24]. Participation levels in V2G are still low due to user concerns about battery wear and cost-effectiveness, with only up to 45% of users expected to engage in V2G by 2050 compared to 67–92% for G2V [1], [25].

To quantify the impact of EV integration on power system adequacy, reliability metrics such as Loss of Load Expectation (LOLE), Expected Energy Not Supplied (EENS), and Expected Demand Not Served (EDNS) are commonly employed [3], [26], [27]. These are especially relevant to Great Britain's (GB's) adequacy-focused reliability standard of ≤ 3 hours LOLE per year. Furthermore, the contribution of smart charging to system security is evaluated using capacity value indicators including Effective Load Carrying Capability, Equivalent Firm Capacity, and Capacity Credit (CC) [28], [29], which collectively help assess how EVs can support system adequacy and meet decarbonisation targets.

This study develops models for uncoordinated, G2V, and V2G charging strategies and integrates them into a Monte Carlo-based probabilistic reliability assessment framework to evaluate the contribution of optimised EV charging to power system security of supply. Residential vehicle travel patterns are synthesised from statistical data to capture diversity in driving behaviour, which is crucial for accurately modelling EV charging demand. In the case studies, inputs from the GB power system are used to quantify the contribution of G2V and V2G to system adequacy for different smart charging participation rates, and to evaluate the impact of EV uptake and wind generation capacity on system reliability.

II. METHODOLOGY

A. System Modelling

Gas-fired, coal-fired, and nuclear generators were modelled as two-state Markov Chains, shown in Fig. 1. Assuming outages and repairs follow a Poisson process, the transition rates λ and μ are constant and equal the reciprocal of the Mean Time to Failure (MTTF) and Mean Time to Repair (MTTR) properties of generators. These rates were multiplied by the simulation time step Δt to obtain transition probabilities for the discrete-time model. Unit availabilities (α) were calculated using (1). Total available conventional power generation at every time period t ($P_{G,t}$) was obtained using (2), where P_i and $s_i \in \{0,1\}$ denote the installed capacity and state of unit i , and N_G is the number of units.

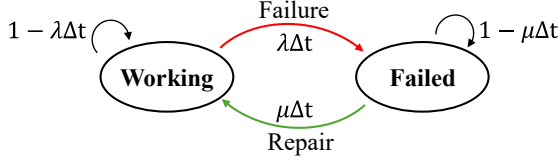


Fig. 1 Discrete-time two-state Markov Model of conventional generators.

$$\alpha = \frac{MTTF}{MTTF + MTTR} = \frac{\mu}{\mu + \lambda} \quad (1)$$

$$P_{G,t} = \sum_{i=1}^{N_G} P_i s_{i,t} \quad (2)$$

Wind and solar generation were modelled following the bias-corrected reanalysis approach in [30] that yields hourly capacity factors obtained from [31] for solar, onshore wind, and offshore wind. These factors were applied to scale the corresponding installed capacities of renewable generation in each simulated time period t . Energy storage availability was assumed to be 90%, while its operation is modelled according to [32] with the aim to minimise Energy Not Supplied during scarcity events while assuming that charging occurs during periods of excess generation. Finally, hourly base demand was obtained from historical data.

B. EV Charging Demand

A primary driver for residential EV charging demand is driving behaviour; Therefore, the demand model was built based on journey data, as for example obtained from [33] in our case studies. Assuming that EVs are charged immediately after the last journey of the day, the statistical data can be transformed into electrical demand for uncoordinated EV charging for a typical weekday and weekend day [5]. This was done for N_l groups of EVs with similar arrival and departure times and assuming a homogeneous residential EV fleet with 50 kWh capacity and access to 7 kW chargers. The resulting average demand curve is shown in Fig. 2.

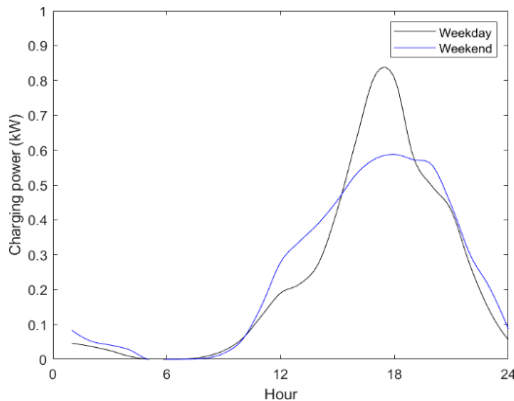


Fig. 2 Average uncoordinated EV charging demand.

The smart charging models optimise the uncoordinated demand curve, as done in [2], to improve system adequacy. The effect of G2V is to flatten the demand curves in Fig. 2 only when a generation shortage occurs, as modelled with (3) – (7). The objective function takes the quadratic form to both minimise the demand and average the load distribution. Notably, constraint (7) ensures that the total energy drawn during a smart charging period is the same as it would have been under uncoordinated charging during that period.

$$\min \sum_{t=t_L}^{t_L+T} (p_t^{base} + \sum_{i=1}^{N_l} (1 - \sigma) N_i p_{i,t}^{EV} + \sum_{i=1}^{N_l} \sigma N_i p_{i,t}^{G2V})^2 \quad (3)$$

$$0 \leq p_{i,t}^{G2V} \leq p^{max}, \forall i, t \quad (4)$$

$$p_{i,t}^{G2V} = 0, \text{ for } t_i^d \leq t < t_i^a \quad (5)$$

$$\sum_{t=t_i^d}^{t_i^a} p_{i,t}^{G2V} \eta^+ \Delta t = (\overline{SoC} - \underline{SoC}) E, \forall i \quad (6)$$

$$\sum_{t=t_L}^{t_L+T} p_{i,t}^{G2V} \Delta t = \sum_{t=t_L}^{t_L+T} p_{i,t}^{EV} \Delta t, \forall i \quad (7)$$

The V2G modelling was performed similarly in (8) – (16), with the exception that contracted EVs are able to discharge to the grid. The SoC in each t was updated with (14) and constrained with (15). Like with G2V, consistency with the energy required under uncoordinated charging was maintained with (16).

$$\min \sum_{t=t_L}^{t_L+T} (p_t^{base} + \sum_{i=1}^{N_l} (1 - \sigma) N_i p_{i,t}^{EV} + \sum_{i=1}^{N_l} \sigma N_i (p_{i,t}^{V2G+} - p_{i,t}^{V2G-}))^2 \quad (8)$$

$$0 \leq p_{i,t}^{V2G+} \leq p^{max}, \forall i, t \quad (9)$$

$$0 \leq p_{i,t}^{V2G-} \leq p^{max}, \forall i, t \quad (10)$$

$$p_{i,t}^{V2G+} = 0, \text{ for } t_i^d \leq t < t_i^a \quad (11)$$

$$p_{i,t}^{V2G-} = 0, \text{ for } t_i^d \leq t < t_i^a \quad (12)$$

$$\sum_{t=t_i^d}^{t_i^a} (p_{i,t}^{V2G+} \eta^+ - \frac{p_{i,t}^{V2G-}}{\eta^-}) \Delta t = (\overline{SoC} - \underline{SoC}) E, \forall i \quad (13)$$

$$SoC_{i,t} = \underline{SoC} E + \sum_{t=t_i^d}^{t_i^a} (p_{i,t}^{V2G+} \eta^+ - \frac{p_{i,t}^{V2G-}}{\eta^-}) \Delta t, \forall i, t \quad (14)$$

$$\underline{SoC} E \leq SoC_{i,t-1} + \left(p_{i,t}^{V2G+} \eta^+ - \frac{p_{i,t}^{V2G-}}{\eta^-} \right) \Delta t \leq E, \forall i, t \quad (15)$$

$$\sum_{t=t_L}^{t_L+T} (p_{i,t}^{V2G+} \eta^+ - \frac{p_{i,t}^{V2G-}}{\eta^-}) \Delta t = \sum_{t=t_L}^{t_L+T} p_{i,t}^{EV} \Delta t, \forall i \quad (16)$$

In the above equations, t_L is the time period when a LOL event occurs and smart charging is employed, T is the length of the operation of smart charging, t_a and t_d are the arrival and departure times, respectively. Then, p^{base} is the system non-EV demand, N_l is the number of EV groups, N_i is the number of EVs in group i , and σ is the participation rate denoting the percentage of EVs participating in smart charging schemes. For G2V, $p_{i,t}^{G2V}$ is the charging demand of each EV in group i at time t . Similarly, $p_{i,t}^{V2G+}$ and $p_{i,t}^{V2G-}$ denote charging and discharging power under V2G. Finally, $\underline{SoC}$ and $\overline{SoC}$ are the minimum and maximum allowed SoC, whereas η^+ and η^- are charging and discharging efficiencies.

C. Probabilistic Framework

Smart charging concepts were evaluated using a probabilistic reliability assessment framework based on time-sequential Monte Carlo simulations. The framework estimates LOLE and EENS from N_Y independently simulated years of system operation. A random system state, as described with (17), was evaluated at every period t with a progression of Δt . Total generation (G_t) and demand (D_t) were computed at every t and used to determine LOL and ENS, according to (18) and (19). The expected values for the reliability metrics were then calculated with (20) and (21).

$$S_t = \{G_{i,t}^{coal}, G_{j,t}^{gas}, G_{k,t}^{nuclear}, G_t^{solar}, G_t^{wind}, G_{i,t}^{ES}, D_t^{base}, D_t^{EV}\} \quad (17)$$

$$LOL_t = \begin{cases} 1, & \text{if } G_t < D_t \\ 0, & \text{otherwise} \end{cases} \quad (18)$$

$$ENS_t = \begin{cases} (D_t - G_t)\Delta t, & \text{if } G_t < D_t \\ 0, & \text{otherwise} \end{cases} \quad (19)$$

$$LOLE = \frac{1}{N_Y} \sum_{n=1}^{N_Y} \sum_{t=1}^{8760/\Delta t} LOL_{n,t} \Delta t \quad (20)$$

$$EENS = \frac{1}{N_Y} \sum_{n=1}^{N_Y} \sum_{t=1}^{8760/\Delta t} ENS_{n,t} \quad (21)$$

The difference between EV charging concepts arises in the treatment of LOL events. With uncoordinated charging, LOL and ENS were recorded as observed, whereas with G2V and V2G, EV charging is first optimised for the duration of the original LOL event before reliability indices were recorded.

Adopting the approach in [32], CC was used to quantify the contribution to security of supply. It represents the amount of conventional generation that could be replaced by contracting EV smart charging capacity to maintain reliability at the same level. As summarised in Fig. 3, first a base LOLE is obtained for the system with uncoordinated EV charging. Then, the Monte Carlo simulation with a smart charging concept of choice was performed, iteratively removing 100 MW of gas-fired generation until the updated LOLE is within a pre-defined tolerance of the base LOLE.

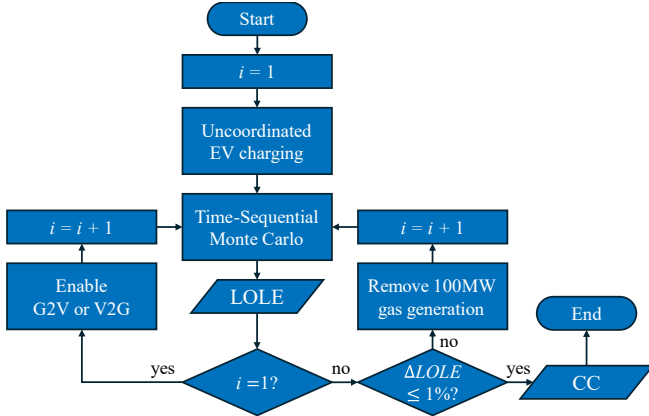


Fig. 3. Framework for quantifying the contribution of smart charging concepts to security of supply.

III. CASE STUDIES

The case studies aim to make general observations on the role and value of smart charging concepts in the context of system adequacy. Nonetheless, inputs were derived from the GB power system in 2022, where only generation units with relatively large capacities were considered. Conventional generation units and their technical parameters listed in TABLE I. are obtained from [28], [34], and [35]. Solar installed capacity was assumed 14.3 GW, onshore and offshore wind 13.4 GW for each [36], and 3.1 GW of energy storage capacity. The half hourly GB demand profile was extracted from [37] with a peak of 46.1 GW. To analyse a future system with a higher EV uptake, the projected number of battery EVs in 2030 in the Future Energy Scenarios (FES) [2] was used, which is 11.9 million.

TABLE I. CONVENTIONAL GENERATION ASSUMPTIONS

Fuel type	Number of units	Installed capacity (GW)	MTTF (h)	MTTR (h)	α (%)
Coal	3	3.8	600	100	86
Gas	45	30.8	1250	60	95
Nuclear	7	7.7	8000	150	98

Based on journey data observations, $N_l = 190$ EV groups were assumed, charging every four days under the conditions that $SoC = 0.3$ and $SoC = 0.95$, with $\eta^+ = \eta^- = 0.9$. The Monte Carlo simulation was implemented in Matlab with $N_Y = 3000$ and $\Delta t = 0.5h$.

A. Evaluation of the Contribution of EV Smart Charging Concepts to Security of Supply

There is significant uncertainty regarding the behaviour of EV users, including their charging habits and willingness to participate in controlled charging. Therefore, in this section, the contribution of G2V and V2G to system adequacy for different smart charging participation rates is evaluated.

Uncoordinated EV charging demand modelling shows that the charging and base load peaks coincide. This results in a total peak demand increase of 8.77 GW, as demonstrated for a 7-day period in Fig. 4. Additionally, the integration of EVs increases the peak-valley difference in the load profile, posing challenges to system adequacy and requiring significant investment in additional generation and network capacity.

In comparison, unidirectional smart charging can shift the peak demand to the valley of the curve as demonstrated in Fig. 5. Instead of starting to charge immediately upon returning home in the evening, EVs absorb energy at night when fewer appliances are in use. This notably flattens the demand curve. As EV participation rate decreases, the peak shaving effect of G2V decreases as well. The load curve could be completely flattened if all electric cars commit to V2G as shown in Fig. 6. This is due to the discharge capability, which allows EVs to supply the grid with remaining electricity in their batteries during high demand periods, potentially preventing LOL events. Similar to unidirectional charging, the effect depends on the participation rate.

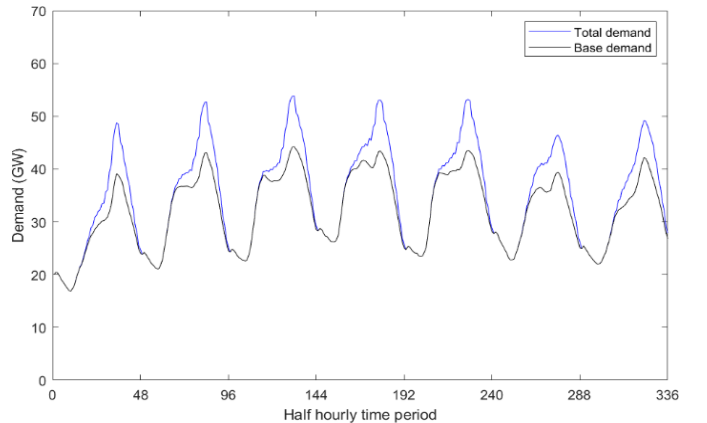


Fig. 4. A 7-day demand curve with uncoordinated EV charging.

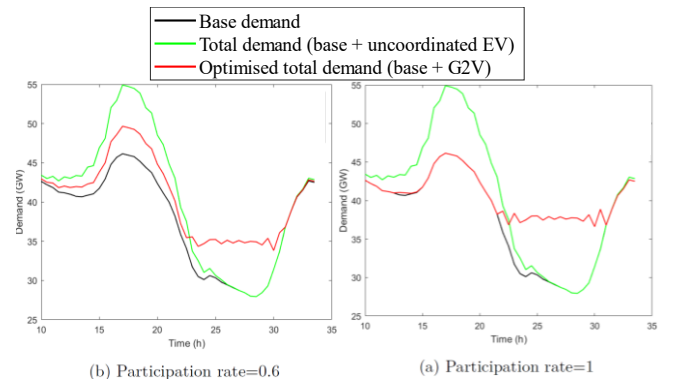


Fig. 5. The impact of G2V participation rate on the system demand curve.

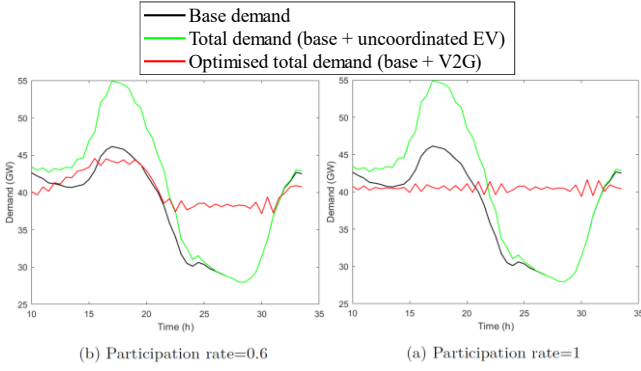


Fig. 6. The impact of V2G participation rate on the system demand curve.

Given the previous observations, the study analysed the contributions of G2V and V2G to system reliability under different participation rates. The results are illustrated in Fig. 7, where the zero-participation rate case corresponds to uncoordinated charging. The results indicate that V2G has significant advantages over G2V in maintaining system reliability. It is also observed that as V2G engagement exceeds 60%, reliability indices remain nearly unchanged. To quantify the capability of smart charging concepts to maintain system operation security under different participation rates, CC was computed and presented in Fig. 8. The results demonstrate that the capacity value of G2V increases consistently with growing participation. For V2G, CC initially increases rapidly due to the discharging capabilities, before its contribution to system adequacy plateaus at high levels of participation.

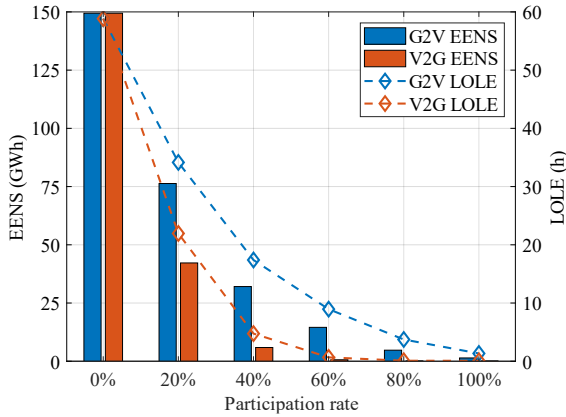


Fig. 7. Effect of smart charging participation rate on reliability metrics.

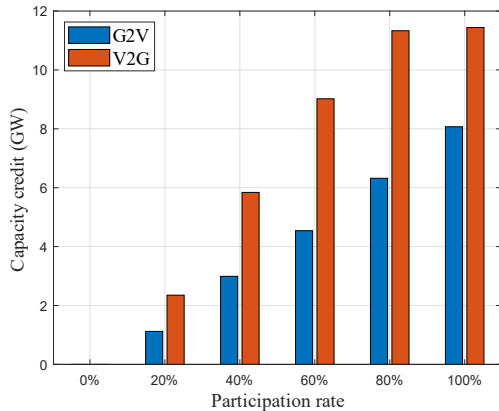


Fig. 8. Capacity credit of G2V and V2G.

B. Investigation of the Impact of Wind Capacity and EV Uptake on System Reliability

In addition to network reinforcements, additional generation capacity will be required to meet the large

electrical demand of the future EV fleet, especially when concentrated during several evening hours coinciding with the system demand peak. As electricity sectors are shifting to renewable energy sources, scaling wind generation will be crucial for many power systems worldwide. Therefore, sensitivities were performed to analyse the impact of increasing wind capacity and residential EV uptake on the contributions of G2V and V2G to security of supply. The assumptions are drawn from the scenario projections in the FES data workbook for 2030 to 2050 [1], with residential EV numbers ranging from 12 million to 30 million in 4.5 million increments, and wind capacity increasing from 26 GW to 130 GW in steps of 26 GW.

In both G2V and V2G scenarios, with the same level of EV penetration, an increase in installed wind capacity initially leads to a quick rise in CC, which then plateaus. For instance, in the G2V scenario, the CC increases by about 10% as wind capacity grows from 26 GW to 52 GW with 30 million EVs integrated into the GB power system. However, this increase diminishes as wind capacity continues to grow. When wind capacity reaches 78 GW, each additional 26 GW of wind power only results in a 3 – 4% increase in security of supply. This effect is more pronounced with higher EV penetration. Identifying the inflexion point is important for power system planners aiming to design a low-carbon system with the socially optimal mix of technologies.

IV. CONCLUSIONS

This paper evaluates the impact of EV integration on the reliability of the GB power system under both uncoordinated and smart charging strategies. Residential charging profiles were derived from realistic weekday and weekend arrival-departure patterns, and optimisation-based models for G2V and V2G were developed to flatten the aggregated demand curve, while maintaining user constraints. Time-sequential Monte Carlo simulations were performed to compute key reliability metrics and to quantify the contribution of smart charging to system adequacy as CC.

Two case studies investigated the effects of smart charging participation rates, EV penetration, and wind generation capacity. The results indicate that both smart charging strategies significantly reduce the occurrence and intensity of LOL events compared to uncoordinated charging, with V2G offering enhanced performance as evidenced by its higher CC. As user participation in smart charging schemes increases, contributions to security of supply grow rapidly but eventually plateau, suggesting technology saturation. Similarly, while G2V and V2G CCs increase with greater EV uptake and wind capacity, marginal gains diminish and eventually stabilise at high wind penetration levels.

Despite its promise, V2G integration faces barriers in regulatory clarity, infrastructure readiness, and user engagement as current charging behaviour remains passive with limited incentives for active participation in grid services. Nevertheless, for the case of GB, the FES pathways involve ambitious levels of V2G required to meet net-zero goals, implying that a strong policy pull for enabling technologies and behavioural shifts can be expected. To maximise system reliability benefits, planners and aggregators should prioritise scaling V2G infrastructure and incentivising participation in smart charging schemes. Strategic coordination between EV deployment and renewable integration will be essential to avoid diminishing returns at high penetration levels.

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