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From bigger batteries to new charging realities

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ABSTRACT

The rapid adoption of electric vehicles (EVs) with increasingly advanced battery technologies is reshaping electricity demand patterns. Yet existing studies often assume static behaviors, overlooking that real-world charging patterns are transient and evolve in response to technological change. This study applies a scenario-aware generative modeling framework to project weekly EV charging demand in Beijing for 2030, capturing behavioral shifts driven by evolving battery technologies, usage patterns, and infrastructure conditions. Results indicate that total charging load could increase by 457–509% compared to a 2021 baseline under two different scenarios of battery size growth. Though medium-power (4–20 kW) charging remains dominant in event frequency, high-power (> 20 kW) charging contributes substantially to loads, implying the growing risk of stress on the power grid in the absence of coordinated scheduling. The proposed framework provides a scalable, data-driven method to simulate EV usage and load patterns and offers valuable insights for transportation and energy planners confronting the rapid electrification of private mobility.

1. Introduction

The accelerating global transition towards electric vehicles (EVs), driven by environmental concerns and policy incentives, is significantly reshaping transportation systems and energy infrastructure worldwide. The rapid growth in EV adoption is accompanied by increased charging demand, creating new challenges for power grid management and infrastructure planning.

Policies and planning decisions regarding EV infrastructure depend critically on multiple factors, including EV battery capacities and consumer charging behaviors (Liao et al., 2023). At the same time, EV adoption is influenced by the availability and adequacy of charging infrastructure (Funke et al., 2019b). Considerable uncertainty remains concerning how future EV users will charge their vehicles, particularly as larger battery sizes-driven by preferences for extended driving range (IEA, 2025) and reduced charging frequency-reshape usage patterns (Zhan et al., 2025). This evolution in battery technologies profoundly impacts users' charging behaviors, usage patterns, and the corresponding infrastructure requirements. As a result, forecasting future charging infrastructure needs requires anticipating changes in user behavior, especially those correlated with battery capacity and usage context. Charging behavior is highly heterogeneous, particularly among urban residents without home charging access, who rely on a mix of public,

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workplace, and shared residential chargers (Gnann et al., 2018; Funke et al., 2019a; Zhan et al., 2025). The heterogeneity, combined with evolving technologies, leads to significant variation in charging frequencies, peak demand loads, and infrastructure needs in future scenarios.

1.1. Related work

Most studies to date rely on historical data and static assumptions, such as universal access to home charging or uniform charging routines, which fail to capture the complexity of real-world behaviors (Hardman et al., 2018; Funke et al., 2019b). Existing approaches to generating EV charging demand for analysis, whether for forecasting or for simulating plausible future patterns, can be grouped into several main categories.

Statistical and stochastic models, such as Monte Carlo simulations and Markov chains, leverage historical data and probability distributions to forecast future charging behaviors and aggregate loads (Nespoli et al., 2023; Shen et al., 2022). These models are computationally efficient and interpretable, but they depend on fixed distributional assumptions and historical patterns, which makes them inflexible to shifts in user behavior and emerging shifts in technology usage, such as the adoption of larger batteries.

Agent-based models (ABMs) simulate individual decision-making processes and interactions in realistic spatio-temporal contexts. They can capture heterogeneous user behaviors and feedback between charging demand and infrastructure. However, they require detailed behavioral and spatial data and rely heavily on modeler assumptions, which can limit their applicability in data-constrained settings (Liao et al., 2023).

Machine learning methods —including Random Forests (RF) and deep neural networks such as Long Short-Term Memory (LSTM) networks —capture complex, nonlinear relationships in large datasets and improve predictive accuracy (Wang et al., 2023a,b). Despite these strengths, they typically produce deterministic outputs, limiting their usefulness for scenario planning and uncertainty quantification, and they require large labeled datasets for training.

Generative models, such as Generative Adversarial Networks (GANs) and Mixture Density Networks (MDNs), learn the underlying distributions of charging sessions, including timing and power profiles, and can generate realistic synthetic scenarios even from moderate-sized datasets. GANs can learn the underlying distribution of charging sessions-including timing and power profiles-and generate realistic synthetic scenarios even from moderate-sized datasets (Tanyıldız et al., 2025; Brusaferri et al., 2022). MDNs excel at modeling conditional distributions, especially useful for representing multimodal behaviors (e.g., different charger types or usage patterns). However, most existing generative models often struggle to capture long-range temporal dependencies, which are critical for sequential, user-level charging forecasts over extended periods.

Empirical evidence has pointed out potential changes in user behavior correlated with battery capacity and usage context. In Germany, Plötz et al. show that EVs with larger battery capacities make disproportionately greater use of high-power chargers, while low-power charging becomes increasingly rare among long-range BEVs (Funke and Plötz, 2017; Gnann et al., 2018). Their techno-economic analysis highlights that as battery capacity increases, users systematically shift charging activity toward faster, higher-rated equipment, mirroring the strong decline of low-power charging in our premium ($\geq 85\,\text{kWh}$) group. Research from California provides additional insight into the behavioral mechanisms underlying charger choice. Tal et al. report that higher charging power is consistently associated with lower arrival state of charge (SOC), and that users of longer-range vehicles both charge less frequently and exhibit a stronger preference for higher charging power (Tal et al., 2020, 2018). Taken together, the evidence from Germany and California reflects general user responses to increasing battery capacity, evolving charging access, and the growing availability of high-power charging infrastructure. This cross-regional alignment strengthens the transferability of our findings and highlights the broader relevance of our projections for other regions undergoing rapid EV adoption.

Additional evidence from more recent European studies further reinforces these patterns. Anderson et al. find that German EV users with higher annual mileage and longer-range BEVs exhibit substantially stronger preferences for higher charging power, even in residential contexts, suggesting that increasing battery capacity amplifies demand for faster charging across multiple use settings (Anderson et al., 2023). Ziras et al., using more than 5500 Danish residential chargers, observe that users increasingly exploit higher available power ratings as infrastructure improves, leading to a doubling of observed peak residential charging power (Ziras et al., 2024). Moreover, large-scale public fast-charging data from Germany (Link et al., 2025) document sustained growth in DC fast-charging utilization, especially for long-range BEVs, confirming internationally that increases in battery capacity are accompanied by a shift toward high-power charging.

1.2. Research objectives and novelty

Our study aims to project charging infrastructure needs and EV usage in Beijing by 2030, reaching an EV adoption rate of 26%, up from the 7.9% in 2021. There remains a clear gap in approaches that effectively integrate scenario flexibility, robust uncertainty quantification, and the ability to accurately capture long-range temporal dependencies inherent in EV charging behaviors. To address these needs, we propose a transformer-based conditional generative modeling framework coupled with Gaussian Mixture Regression (GMR). The transformer architecture excels at modeling sequential data over extended periods due to its self-attention mechanism, making it particularly effective for representing detailed temporal charging patterns (Koohfar et al., 2023). Furthermore, integrating GMR enhances the model's capability to represent the inherent uncertainty and variability across diverse EV user segments and scenarios, thus providing more reliable and actionable insights for infrastructure planning.

The main contributions of this paper include: (a) We develop a transformer-GMR framework that learns user charging behaviors from empirical data and generates realistic demand under diverse scenario assumptions (e.g., larger battery sizes). The approach com-

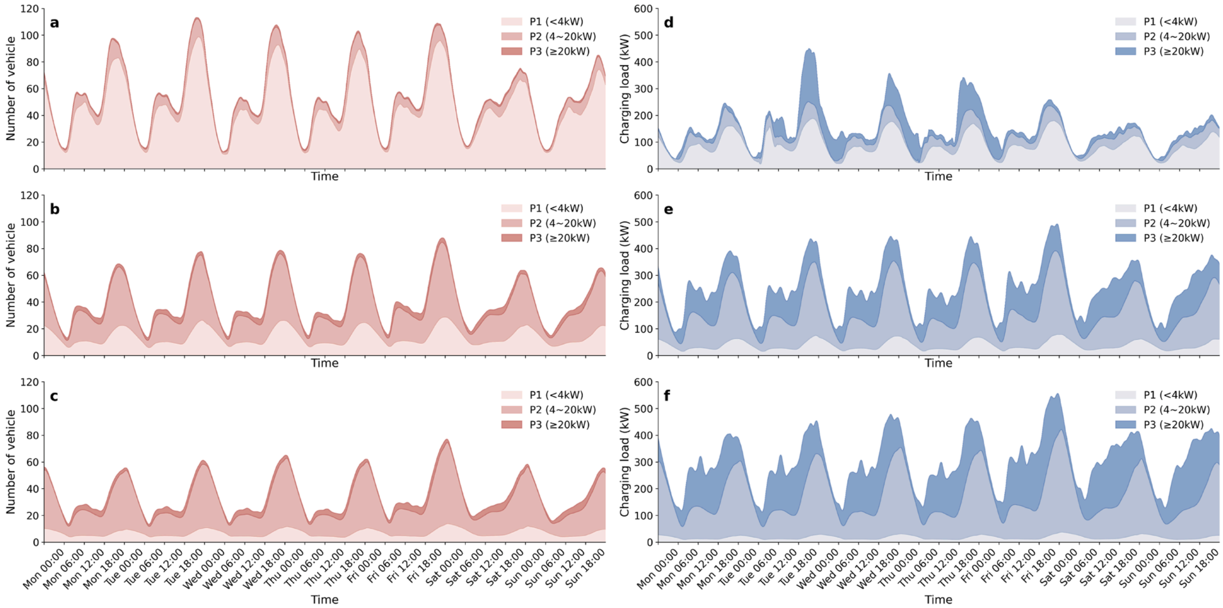

Fig. 1. Seven-day (Monday to Sunday) charging events per 1000 vehicles for (a) small-, (b) medium-, and (c) large-battery EV users, and corresponding charging load per 1000 vehicles for (d) small-, (e) medium-, and (f) large-battery users.

bines individual-level behavioral simulation with aggregate demand forecasting, enabling macro-level temporal projections without assuming users are homogeneous or modeling each variable in isolation. (b) We explicitly incorporate the effect of growing battery capacities on charging frequency and intensity into scenario definitions, capturing battery-size-dependent behavioral shifts that are largely overlooked in existing models.

Note that we do not claim to predict future charging demand with point accuracy-individual charging decisions at different times are inherently uncertain and subject to numerous unobservable factors. Rather, our framework is designed for scenario analysis: exploring 'what if' outcomes under alternative battery capacity trajectories to support infrastructure planning and policy deliberation, retaining substantial interpretability. Such interpretability comes from i) exogenously specified battery capacity scenarios with transparent extrapolation methods, ii) activity frequency constraints directly derived from empirical distribution, and iii) the Gaussian Mixture Regression component modeling conditional distributions that can be inspected and validated against real-world charging patterns. Thus, the framework combines data-driven flexibility for capturing complex sequential structure with scenario transparency and empirical grounding.

The remainder of this paper is structured as follows: Section 2 introduces the dataset, while Section 3 presents the transformer-GMR modeling framework. Section 4 analyzes and discusses scenario-based forecasts and their implications for infrastructure planning. Finally, Section 5 concludes and summarizes the key findings and proposes future research directions.

2. Data

This study applies a dataset obtained from the National Big Data Alliance of New Energy Vehicles Lab, encompassing the operational data of over 314,000 private EVs in Beijing from November 1, 2020, to October 31, 2021. We retained those vehicles that recorded at least 365 usage events (driving and charging) over the year and excluded the remainder (which may suffer from data-transmission issues). The resulting dataset includes over 232,000 vehicles-approximately 74% of the total private EV fleet in our dataset. These vehicles span a wide range of battery capacities, from 9.2 kWh to 84 kWh, reflecting a substantial diversity in EV model types and configurations.

The data structure and charging power classification are empirically determined, as detailed in our previous work (Zhan et al., 2025). We categorize charging events into three power levels, P1, P2, and P3, based on clustering of observed charger types, corresponding to slow (< 4 kW, P1), medium (4–20 kW, P2), and fast (≥ 20 kW, P3) charging.

We divide users into three battery-capacity groups: small (< 25 kWh), medium (25–55 kWh), and large (55–85 kWh). The charging events and charging load for each group are shown in Fig. 1. Users of larger-battery EVs engage in fewer charging sessions per day compared to those with smaller batteries. Moreover, the shares of mid-power (P2) and high-power (P3) charging increase with battery size, suggesting that users of large-battery vehicles prefer higher-power charging options. In contrast, small-battery EV users tend to charge more frequently and rely more on low-power (P1) charging.

Our data also suggests that as battery capacity increases, the frequency of charging events among overall EV events (charging, driving, and parking) initially decreases and subsequently stabilizes. This suggests that beyond a certain battery capacity, the frequency of charging events may reach a steady state (Table 1). The assumption of charging-frequency stabilization is empirically supported by

Table 1
The frequency of charging, driving, and parking for EVs with different battery capacity bins (E_{bin}), including percentage of data in each bin.

E_{bin} (kWh)	Charging (%)	Driving (%)	Parking (%)	Percentage (%)
5–15	11.98	41.44	46.59	0.07
15–25	10.69	40.09	49.22	1.14
25–35	8.83	43.72	47.45	5.04
35–45	6.28	45.20	48.52	10.00
45–55	6.18	46.26	47.56	58.24
55–65	4.66	47.72	47.62	9.66
65–75	4.83	47.44	47.73	11.20
75–85	5.34	46.79	47.87	4.66

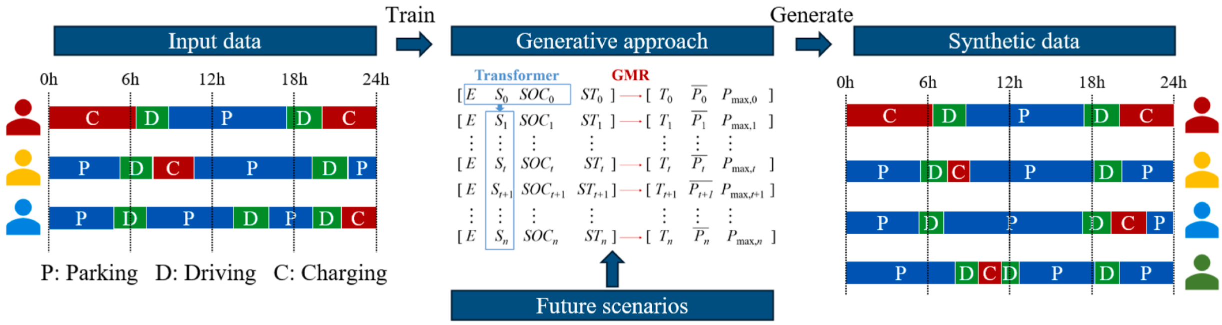

Fig. 2. The transformer–GMR model generates future charging behavior by learning from existing user groups and adapting to scenario changes, including the appearance of a new premium-battery group.

the 2021 Beijing data, which show that while charging-event frequency declines with battery capacity up to 65 kWh, it subsequently plateaus at approximately 4.6–5.4%, providing a data-driven boundary condition for extrapolating behavior of premium-capacity EVs (> 85 kWh).

3. Methods

We develop a scenario-aware generative modeling framework to forecast future passenger EV charging behavior under varying battery capacity conditions. The core of the framework is a transformer-based autoregressive model, coupled with GMR, designed to generate weekly sequences of driving, parking, and charging events for private passenger EVs. The framework is trained on detailed empirical data, capturing the heterogeneity in EV usage behavior across vehicle types and urban contexts.

3.1. *Transformer model for activity sequences*

To generate realistic future usage scenarios, we develop a conditional generative model that produces one-week sequences of vehicle activity. The generated data mirrors the existing groups while also extrapolating to patterns not present in the original dataset, including those associated with premium-battery vehicles absent from historical data (Fig. 2).

The conditional autoregressive transformer model generates sequences of EV activity states (“C”, “D”, “P”), where each symbol represents a token - the fundamental unit of information processed by the model. In our case, a token corresponds to one 15-minute segment of an EV’s weekly activity, encoded as either charging (C), driving (D), or parking (P). A full weekly sequence, therefore, consists of up to 160 such tokens. The model learns to generate these sequences one token at a time using self-attention, which allows it to consider the entire previously generated context when predicting the next activity state. Each token is mapped into a continuous embedding space and augmented with conditioning variables — battery capacity (E), initial energy state (S_0), and initial SOC (SOC_0) — as well as positional encodings that represent its position in the week. This allows the transformer to capture both temporal structure and contextual dependence when producing realistic EV activity patterns.

The Transformer decoder is built with two masked multi-head self-attention layers. Masking ensures the model cannot “look ahead” at future tokens when predicting the next EV activity, thereby preserving the autoregressive structure. Through multi-head self-attention, the decoder learns patterns and dependencies across the entire history of tokens — for example, how an EV’s driving or charging earlier in the week shapes its later charging/discharging behavior.

To mitigate class imbalance among state types, we train the model using a weighted cross-entropy loss function and optimize it using the Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.98$, learning rate = 0.0001). A `LambdaLR` scheduler implements a learning rate warm-up over the first 10% of training steps, followed by a linear decay, enhancing training stability. Gradient norms are clipped to a maximum of 1.0 to avoid gradient explosion.

Inference is conducted using autoregressive sampling with temperature scaling, coupled with a repetition penalty to discourage unrealistic token sequences. We further constrain output sequences based on empirical activity frequencies stratified by battery capacity (Table 1) to ensure synthetic outputs remain behaviorally plausible, i.e., we constrain output sequences using empirical activity frequencies stratified by battery capacity (Table 1). In line with observed data, we assume that beyond the highest battery capacity range in the training set, further increases in capacity do not substantially change charging event frequency, and this plateau value is applied as a fixed constraint in the model.

After the Transformer generates an activity state for each segment, the start time and SOC are updated using deterministic update rules:

$$ST_{t+1} = ST_t + T_t \tag{1}$$

$$SOC_{t+1} = SOC_t + \frac{\bar{P}_t \times T_t}{E} \tag{2}$$

where $t = 0, 1, \cdots, n-1$ and E represents the nominal battery capacity of the EV. S_t is the state of the vehicle at the t-th segment (C = charging; D = driving; P = parking). SOC_t represents the SOC at the start of the t-th segment. ST_t represents the start time of the t-th segment, converted into a timestamp within the current week. T_t is the duration of the t-th segment. $P_{\mathrm{avg},t}$ represents the average power during the t-th segment (positive for charging, negative for discharging). $P_{\mathrm{max},t}$ represents the maximum power during the t-th segment (positive for charging, negative for discharging). n represents the total number of segments in one week.

3.2. Gaussian mixture regression for segment attributes

To assign duration (T_t) and power ($\overline{P}_t$) to each segment, we employ GMR to model the joint probability distribution between the condition and target variables of EV segments. Input (condition) variables include battery capacity (E), current activity state (S_t), initial SOC (SOC_t), and start time (ST_t), while target variables include duration (T_t), average power ($P_{\mathrm{avg},t}$), and maximum power ($P_{\mathrm{max},t}$).

A Gaussian Mixture Model (GMM) is first fitted to the combined training examples of condition and target variables, and conditional distributions are derived using standard properties of multivariate Gaussians. Hyperparameters (number of mixture components, covariance type) are tuned using grid search and cross-validation, maximizing out-of-sample R^2 performance. When generating new segments, GMR enables conditional sampling of segment attributes, preserving the probabilistic structure observed in real-world data.

3.3. Scenarios assumptions

To project future EV charging loads, we construct two scenarios for the year 2030 based on projected EV stock and the trends of battery capacity distributions. The projected stock of electric private vehicles in 2030 is estimated based on GDP and ownership trends, as detailed in Appendix A.

Battery capacity distributions are derived from historical stock data between 2019 and 2022, rather than new vehicle sales. Normal distributions are fitted to the annual distributions, yielding yearly mean (μ) and standard deviation (σ) of battery capacity. Two extrapolation methods-linear and logarithmic regression-are used to project these values to 2030. The linear extrapolation defines a high-growth scenario (Scenario 2030-H), while the logarithmic extrapolation defines a low-growth scenario (Scenario 2030-L). Thus, in the low- and high-growth scenarios for 2030, 20.5% and 45.3% of users, respectively, have battery capacities exceeding 85 kWh (premium group), compared with no battery capacities exceeding 85 kWh in 2021. Details of the fitting process and the resulting battery capacity distributions are provided in Appendix B (Figs. B.2 and B.3).

As a consistency check, these stock-level trends align with the sustained increase in battery capacities reported for new EV sales in the IEA Global EV Outlook (2020–2025): a clear increase in average battery capacity, rising from 37 kWh in 2018 to 44 kWh in 2019, 55 kWh in 2020, and approximately 65 kWh by 2024. An expected lag between sales and fleet composition is present. Fleet turnover mechanisms are not explicitly modeled; instead, the scenarios aim to provide transparent, data-driven bounds for plausible future fleet-level battery capacity distributions.

3.4. Synthetic data generation

The synthetic data generation proceeds as follows (Fig. 3). First, individual battery sizes are randomly sampled from the scenario-specific distributions, with sampling stratified across energy bins to preserve their empirical probability masses (Table B.2). Battery size values are sampled uniformly within each bin. Next, initial SOC (SOC_0), activity state (S_0), and segment start time (ST_0) are sampled from empirical distributions. These variables serve as input conditions for the transformer-GMR model.

The Transformer component generates a weekly sequence of vehicle states (charging, driving, parking), while the GMR module assigns durations and power values to each segment. The resulting sequences reflect behaviorally realistic EV usage under future scenario conditions and form the basis for forecasting aggregate charging loads and infrastructure requirements. For validations of the transformer-GMR model performance, see Appendix C.

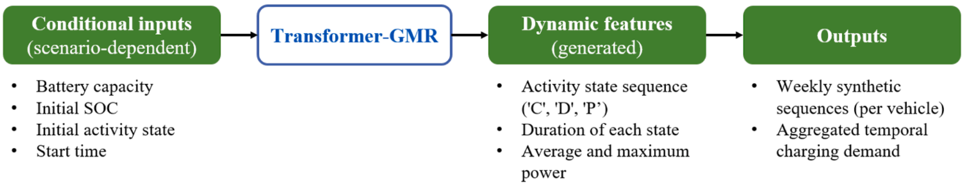

Fig. 3. Inputs, features, and outputs in the transformer-GMR generative framework. Green boxes represent the data elements provided to or generated by the model, while the blue box represents the Transformer–GMR module that takes scenario-dependent inputs and generates dynamic features and outputs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

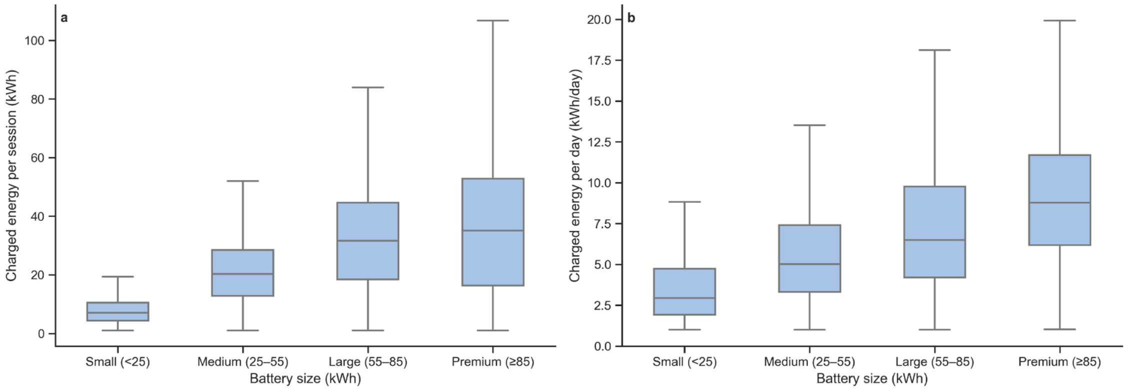

Fig. 4. Distribution of charged energy per session (a) and per day (b) by battery capacity group in 2030.

4. Results and discussion

This section presents projections of EV charging demand for 2030, based on the generative outputs of the validated transformer-GMR model. The analysis examines both user-level charging behaviors (Section 4.1) and aggregate load patterns under two battery size growth scenarios (Section 4.2).

4.1. User-level charging behaviors

Charging behaviors vary substantially across vehicle segments, particularly by battery capacity. Fig. 4 shows an increasing trend of charged energy per session and per day with growing battery capacity. Both the per-sessions charged energy and total daily charged energy in the synthetic data (2030-H/L) closely match those in the real data (2021) shown in Fig. C.3, indirectly confirming the validity of the model-generated data. The results for the largest battery capacity (premium-battery) are simulated in the absence of empirical data, demonstrating the model's ability to realistically extrapolate to unobserved scenarios. This capability allows us to predict how charging behaviors would evolve when battery capacities exceed the range of the actual data.

To further examine differences in charging behavior by battery size, Fig. 5 presents the synthetic initial SOC by charger level and battery capacity group in 2030. For all vehicle groups, the use of higher charging power is generally preceded by a lower SOC at the start of charging. For example, the median SOC_0 for P1 charging is usually higher than for P2, and the median for P2 is higher than for P3, indicating that users tend to start high-power charging at lower SOC levels.

Within each charger level (P1, P2, P3), the distributions of SOC_0 differ significantly among the battery capacity groups (small, medium, large, premium), as confirmed by Kruskal–Wallis tests (all $p < 0.001$). These results indicate that battery size influences charging behavior regardless of charger type, although post-hoc comparisons show that the magnitude and statistical significance of differences vary by charger level, with the clearest distinctions at low and medium power. The statistical tests of these results are in D. As a reference, real-world SOC_0 distributions for 2021 by charger level and battery group are shown in Fig. C.4, allowing for direct validation and comparison with the synthetic scenario results.

Fig. 6 illustrates the synthetic charging frequency and total charging load per 1000 vehicles for users with the premium-battery group ($\geq$ 85 kWh). Compared to the EV population in 2021 (Fig. 1), this new group is expected to charge less frequently but has a significantly higher energy requirement per session. This suggests increased battery capacity extends the driving range between charges but results in larger energy transfer when charging occurs. Charging activity among premium-battery users remains temporally concentrated in the evening, particularly between 20:00 and 00:00, which aligns with typical end-of-day routines and contributes to residential peak demand. The distribution of charging power levels reveals an important asymmetry: while most charging events occur at medium power levels (P2: 4–20 kW), a relatively small number of high-power sessions (P3: $\geq$ 20 kW) account for a disproportionate share of the total load. In contrast, low-power charging (P1: $<$ 4 kW) is nearly absent in this group of EVs.

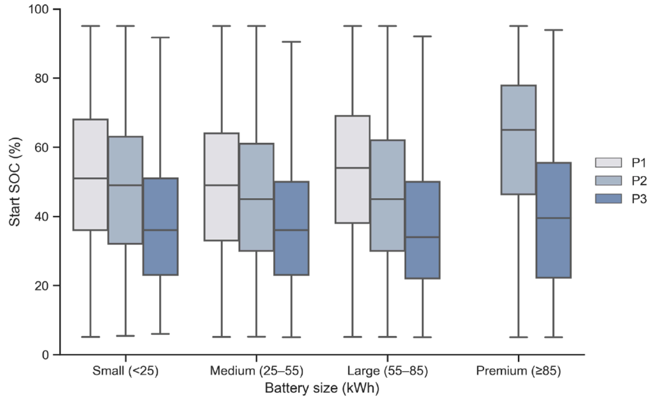

Fig. 5. Synthetic charging initial SOC (SOC_0) by charger level and battery capacity group in 2030. P1 in the Premium (≥ 85 kWh) group is excluded due to a relatively negligible sample size (< 0.0001%), making statistical inference unreliable.

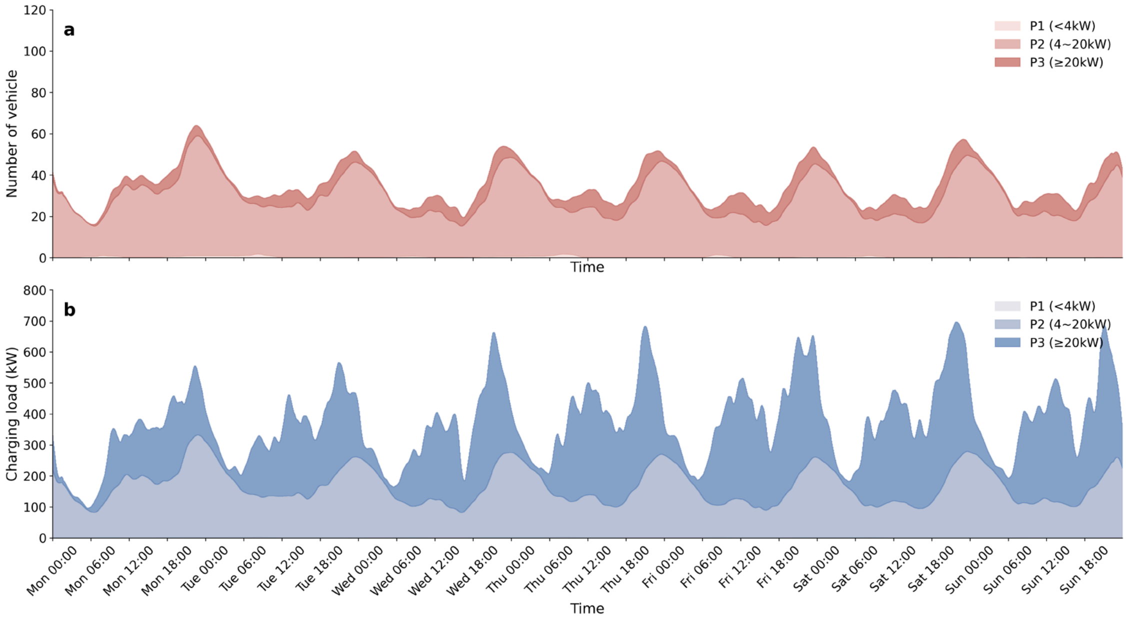

Fig. 6. Synthetic 7-day (a) charging frequency and (b) charging load per 1000 vehicles for premium-battery users (≥ 85 kWh) in 2030.

4.2. Aggregate charging patterns and infrastructure implications

Fig. 7 shows projected charging activity in 2030 under two battery capacity scenarios, compared against 2021 baseline data (dashed lines). Fig. 7(a)–(b) illustrate the number of charging vehicles over a seven-day period for the low-growth (2030-L) and high-growth (2030-H) scenarios, respectively. These are disaggregated by charging power level. Fig. 7(c)–(d) display the corresponding charging loads, measured in megawatts (MW).

Both scenarios exhibit substantial increases in total charging activity relative to 2021, reflecting a combination of EV stock growth and a shift toward higher battery capacities. In Scenario 2030-L, total weekly charging load increases by approximately 457% compared to the baseline. In Scenario 2030-H, which assumes more rapid battery capacity growth, the increase reaches approximately 509%. Although Scenario 2030-H involves slightly fewer charging events due to the higher proportion of premium batteries (resulting in longer driving ranges), the energy transferred per session is larger, leading to a higher overall load. Likewise, daily charging energy consumption in Scenario 2030-H surpasses that of 2030-L by 9.25%, accompanied by a higher utilization rate (by 5.29%) of high-power charging (≥ 20 kW).

The temporal patterns in both scenarios show strong clustering of charging activity during evening hours, particularly between 18:00 and 00:00 (Fig. 7). Peak loads are most pronounced on Friday evenings, while weekend patterns exhibit broader peaks and more temporal flexibility. The majority of charging events occur at medium power levels (P2: 4–20 kW); however, high-power charging

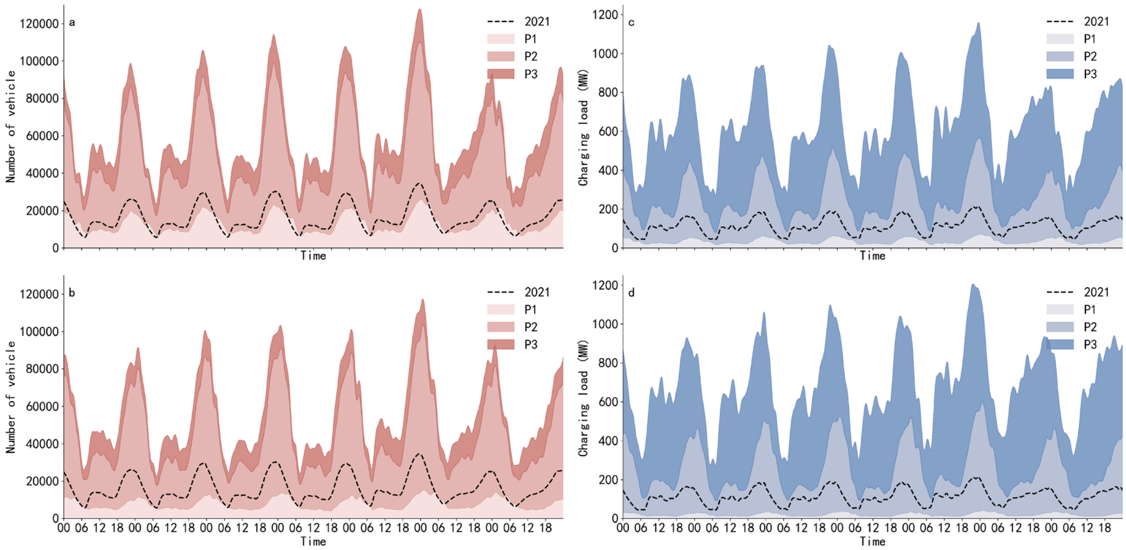

Fig. 7. Projected charging activity under 2030 scenarios: (a) charging events – Scenario 2030-L, (b) charging events – Scenario 2030-H, (c) charging load – Scenario 2030-L, (d) charging load – Scenario 2030-H. Dashed lines represent 2021 baseline values for comparison.

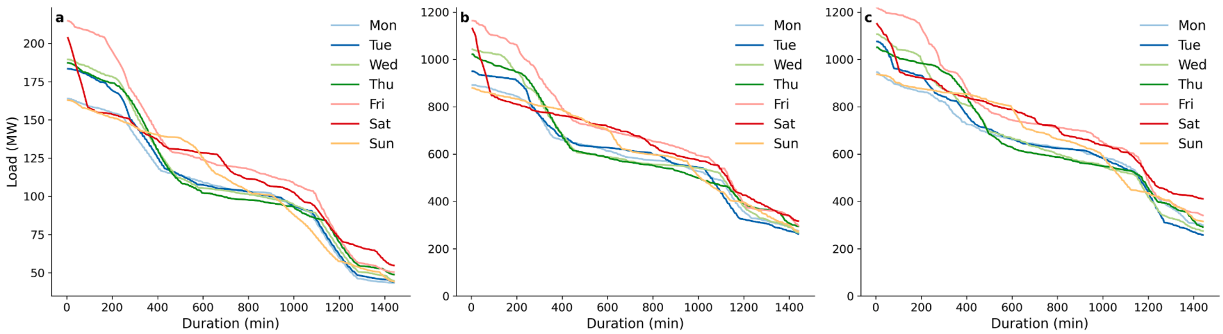

Fig. 8. The daily load duration curves (LDVs) for each day of the week in (a) 2021 baseline, (b) 2030-L, and (c) 2030-H scenarios.

(P3: ≥ 20 kW) contributes a disproportionately large share of the total load, especially during peak periods. Low-power charging (P1: < 4 kW) remains marginal across all scenarios.

Our two scenarios encode both growth in the BEV fleet and a distributional shift toward larger batteries. To disentangle the contribution of battery capacity from fleet size, we construct a counterfactual scenario that applies the 2030 vehicle stock to the 2021 battery capacity distribution (red curve in Fig. E.1). The difference between this counterfactual and the two 2030 scenarios isolates the effect of evolving battery capacities. Under the counterfactual, the number of charging vehicles is consistently higher than in either 2030 scenario, yet aggregate charging load is lower across all time periods. This pattern reflects the behavioral dynamics associated with battery size: smaller-battery vehicles charge more frequently but transfer less energy per session, whereas the larger-battery fleets projected for 2030 charge less often but draw substantially more power when they do. The comparison confirms that battery capacity growth—not merely fleet expansion—is a primary driver of the elevated peak loads and shifting temporal profiles observed in the 2030 projections.

To examine the persistence of high-load conditions, Fig. 8 presents the daily load duration curves (LDVs) for each day of the week. Both scenarios show substantial increases in peak load compared with the 2021 baseline: 442% in Scenario 2030-L and 467% in Scenario 2030-H. Scenario 2030-H also records a peak load about 4.73% higher than Scenario 2030-L, highlighting the additional infrastructure pressures that rapid battery capacity growth could place on peak power management.

4.3. Discussion

The analysis presented in this study highlights significant implications for future EV infrastructure planning and grid operations, given the anticipated trends in vehicle electrification and battery capacity growth. Historical data and projections by authoritative sources such as the International Energy Agency (IEA) indicate that continuing technological advancements, coupled with policy support and consumer adoption, are expected to substantially increase the penetration of EVs equipped with larger battery sizes by

2030 (IEA, 2025). This widespread shift toward higher-capacity batteries is expected to influence charging behavior, as empirical evidence indicates that drivers with greater battery range charge less frequently (Rainieri et al., 2023), thereby underscoring the importance of incorporating battery-size effects into infrastructure planning.

Vehicles with larger batteries tend to charge less frequently but require substantially higher energy per session. This behavior confirms earlier expectations that extended driving range would reduce charging frequency, but it also means each charging session can draw much higher power, creating a marked dependence on faster charging options. Such a shift diverges from early projections that assumed most charging would occur at slow home-charger rates (Hardman et al., 2018). It implies a different temporal load distribution and introduces new challenges for grid stability and peak demand management, echoing concerns raised in previous EV–grid impact studies (Li et al., 2025).

Vehicles with larger batteries tend to charge less frequently but require substantially higher energy per session. This behavior confirms earlier expectations that extended driving range reduces charging frequency (Poupinha and Dornoff, 2024), but it also implies that each charging session can draw much higher power and create a stronger dependence on fast charging options. Importantly, our simulated driving sequences also reveal that vehicles with higher battery capacities exhibit longer driving durations between charges and longer total daily driving time. Specifically, large-battery vehicles exhibit driving durations between consecutive charging events that are 201.7% longer than those of small-battery vehicles, and their total daily driving time is 50.9% higher. Although our framework does not directly predict kilometers traveled, driving duration and distance are strongly positively correlated in empirical mobility datasets; therefore, it is reasonable to infer that larger-battery EVs are likely to be driven more kilometers as well (Brancaccio and Deflorio, 2023). This qualitative direction of the effect is supported by our scenario outputs. At the same time, evidence indicates that most high-income countries experience plateau in total driving distance (Yeh et al., 2022; Schafer and Victor, 2000). While it is difficult to predict precisely when such a plateau might occur in Beijing, this effect should be considered in interpreting the long-term implications of battery-capacity growth. It is also worth noting that larger battery capacities provide users with greater temporal flexibility in charging, which could, in principle, support load balancing. Despite our results suggesting that charging activity remains strongly concentrated during evening hours across all battery capacity groups (Figs. 6 and 7), behavioral interventions such as time-of-use pricing (Yang et al., 2024) or managed charging programs could help unleash this potential benefit.

The behavioral responses captured by our framework-reduced charging frequency and increased preference for high-power charging among users with larger batteries-are not opaque 'black box' relationships, but reflect economically intuitive user responses that have been documented across multiple regions and market contexts. Users with greater battery range experience reduced range anxiety, enabling them to defer charging until more convenient opportunities arise and to favor faster charging options when they do charge. The consistency of these patterns in empirical studies from Germany (Funke and Plötz, 2017; Anderson et al., 2023), California (Tal et al., 2020), and Denmark (Ziras et al., 2024) suggests they represent general behavioral tendencies rather than artifacts of any particular dataset or modeling approach. At the same time, we acknowledge that our framework does not explicitly model the mechanisms driving future increases in battery capacity, such as fleet turnover, consumer preferences, or policy incentives (Yang et al., 2024), nor does it capture potential feedback effects between infrastructure availability and adoption patterns. These dynamics lie outside the scope of this study; our contribution is to provide a empirically grounded tool for exploring how charging demand patterns would evolve given projected battery capacity distributions as scenario inputs. Should growth in stock battery capacity slow, a 'low-' or 'no-battery-growth' scenario could readily be incorporated within the same framework.

High-power charging infrastructure ($\geq$ 20 kW) will need to be scaled up and strategically sited to accommodate these higher loads, particularly during evening hours when most charging occurs. Our projections show pronounced peaks in EV charging demand during roughly 18:00–24:00 (with the highest on Friday night), overlapping with residential electricity peaks. This temporal clustering aligns with real-world charging patterns observed in other regions and could severely stress local grids if left unmanaged (Lehtinen et al., 2020). Therefore, planners should incorporate robust peak-shaving measures, such as smart charging incentives, time-of-use pricing, demand response programs, and targeted grid upgrades or energy storage, to mitigate these surges.

Furthermore, the shift to premium-battery EVs (> 85 kWh) amplifies the importance of a robust fast-charging network. As our results indicate, charging sessions become less frequent for these users but significantly more energy-intensive, necessitating fast-charging infrastructure that is both reliable and widely available. Indeed, it echoes arguments that extending vehicle range should go hand-in-hand with investing in fast-charging facilities to support mass EV adoption (Funke et al., 2019a). Proactive measures, such as network redundancy, increased site capacities, and strategically located high-power chargers, are essential for mitigating localized congestion and ensuring user convenience.

A key contextual consideration is that the empirical data used in this study, collected in Beijing between 2020 and 2021, reflect a charging environment that differs in meaningful ways from both current conditions and other regions. First, battery capacities during this period were smaller on average than those increasingly common in China, Europe, and the United States today. Because our empirical charging patterns are estimated from this lower-capacity fleet, the projected fast-charging demand should be interpreted as conservative: newer EV cohorts with larger batteries are likely to rely even more on high-power charging than is captured in our baseline data. Second, evidence from our earlier multi-city analysis of large Chinese cities (Zhan et al., 2025) indicates that Beijing's distributions of nominal battery energy, daily driving distance, and charging power are broadly comparable to those of other cities, even though Beijing exhibits a higher rate of private EV adoption. This suggests that the behavioural patterns we derive are not unique to Beijing, but are representative of mature urban EV markets in China. Third, Beijing and other dense Chinese cities have relatively limited home-charging accessibility for apartment dwellers, leading to greater reliance on public and workplace chargers compared with many European and United States cities, where overnight home charging in detached or semi-detached housing is more prevalent (Hove and Sandalow, 2019). These structural differences imply that the temporal charging patterns observed here may not directly generalise to low-density contexts with high home-charging penetration today. However, as EV adoption increases and a growing share of households in European and US cities live in multi-unit dwellings without dedicated parking, reliance on public charging is likely to rise (Baldwin et al., 2024). In that sense, our results can be viewed as informative for the future evolution of charging demand in high-density cities beyond China, while the contextual differences outlined above are important for interpreting the generalisability and transferability of the projected results.

In addition, the definition of fast charging adopted in this study, set at 20 kW and above, corresponds to the charging power levels prevalent in the empirical dataset and the public charging infrastructure available in 2020 and 2021. However, the global charging landscape is evolving rapidly. Fast and ultra-fast charging systems rated at 150 or even 350 kW are increasingly available in the US and Europe. Although the modeling framework presented here can incorporate higher power categories in future scenarios, it is important to emphasize that the infrastructure implications associated with these much faster charging levels, such as local transformer loading, feeder constraints, and spatial clustering at stations, are likely to be far more severe than the impacts captured in this analysis (Tayri and Ma, 2025). Therefore, the present results should be interpreted as a lower-bound estimate of future fast-charging impacts, reinforcing the need for follow-up research exploring ultra-fast charging infrastructure requirements.

Finally, it is worth reflecting on the role of AI methods in policy-relevant forecasting, a concern that merits careful consideration. We acknowledge that the use of data-driven approaches in contexts that require explanatory clarity can be problematic if these methods obscure the mechanisms underlying projected outcomes. Traditional EV charging forecasts (e.g., Monte Carlo simulations and Markov chains) offer greater transparency in their assumptions, but they rely on fixed distributional forms and historical usage patterns, limiting their ability to account for behavioral shifts induced by technological change, such as larger batteries (Akil et al., 2022; Li and Li, 2025). The Transformer–GMR framework attempts to balance these concerns by retaining key interpretable elements: battery capacity scenarios are exogenously defined through transparent extrapolation methods (Fig. B.3), activity frequency constraints are derived from empirical distributions (Table 1), and the GMR component provides conditional distributions that can be directly inspected and validated. The transformer handles sequential dependencies in user behavior, a task that would otherwise require strong parametric assumptions difficult to justify empirically, but does not replace the scenario structure that ultimately drives the policy-relevant variation in outputs. We also do not claim to predict individual charging decisions at 15-minute resolution with point accuracy; such predictions are inherently uncertain and subject to numerous unobservable factors. Rather, our framework is designed for scenario analysis, exploring "what if" outcomes under alternative battery capacity trajectories. This framing aligns with the established role of scenario-based modeling in supporting deliberation among planners and policymakers, even when precise prediction is infeasible. Fully end-to-end methods risk limiting transparency, and striking an appropriate balance in applying AI methods is especially important in policy contexts.

5. Conclusion

This study introduces a scenario-aware generative framework that combines a transformer and GMR to produce behaviorally realistic forecasts of EV charging demand. Trained on a large-scale dataset of private EVs in Beijing, the model reproduces observed heterogeneity across battery capacity groups and extrapolates to a premium-battery segment absent in the historical data. Under two battery-growth scenarios for 2030, total charging load increases by 457–509% relative to 2021, while peak load rises by 442% (2030-L) to 467% (2030-H). Although medium-power charging remains dominant by event count, high-power charging contributes a disproportionate share of load, especially during evening peaks between 18:00 and 00:00.

These findings imply that planners should anticipate substantially higher evening peaks and a thicker sustained load across the week, prioritize the siting and sizing of mid- and high-power charging, and pair capacity expansion with peak-mitigation measures such as managed charging, demand response, and targeted storage.

This study has several limitations. First, the analysis focuses on private EVs in Beijing during 2020–2021, and transferability to other cities, user segments, or later years requires further investigation. Second, the model operates at the temporal and user-sequence level and does not capture spatial network constraints, such as station-level congestion or grid feedback loops. Third, based on observed data, we assume that once battery capacity exceeds a certain threshold, further increases do not lead to notable changes in charging event frequency. This plateau effect is used in the model to avoid unrealistic extrapolation for very large battery sizes. However, this assumption should be revisited and updated as newer data become available.

Future work will focus on optimizing EV charging schedules, evaluating various charging strategies, and incorporating additional influencing factors such as user socioeconomic characteristics, spatial charging network configurations, policy interventions, and dynamic grid management strategies to support sustainable electrification growth.

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CRediT authorship contribution statement

Weipeng Zhan: Writing – original draft, Visualization, Validation, Software, Methodology; **Yuan Liao:** Writing – review & editing, Software, Methodology; **Sonia Yeh:** Writing – review & editing, Supervision, Project administration; **Junjun Deng:** Supervision, Resources, Funding acquisition, Conceptualization; **Zhenpo Wang:** Supervision, Data curation; **Dingsong Cui:** Data curation, Conceptualization.

Declaration of competing interest

The authors declare no competing financial or non-financial interests.

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During the preparation of this work, the author(s) used ChatGPT in order to refine the language use. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Appendix A. Projected EV stock in 2030

Accurately projecting future EV charging demand requires reliable estimates of vehicle ownership and electrification rates. Following established methods in vehicle demand forecasting, we model private vehicle ownership as a function of gross domestic product (GDP) using the Gompertz function:

$$V_y = V^* \times \exp\left(\alpha \times \exp\left(\beta \times GDP_y\right)\right) \quad (A.1)$$

Where V_y is the vehicle ownership per capita in year y, V^* is the final target of vehicle ownership per capita, and GDP_y denotes the per capita GDP in year y. The parameters α and β are estimated using official statistics from 2019 to 2023 (Table A.1). This functional form has been shown to perform well in diverse empirical settings, including in regions with constrained historical data (Yeh et al., 2022).

Using projected values for GDP per capita and population in 2030, total private vehicle stock in Beijing is estimated at 7.94 million (Table A.1). Assuming an electrification rate of 26% -consistent with stated policy targets-the projected EV stock reaches 2.06 million.

Table A.1
GDP per capita, population, private car ownership, and EV penetration in Beijing from 2019 to 2030.

Year	GDP per capita (10^4 RMB)	Population (10^6)	Private car per capita	Private car ownership (10^6)	EV penetration (%)
2019	16.4428	21.536	0.23096	4.9740	4.63
2020	16.4856	21.890	0.23455	5.1342	6.55
2021	18.3654	21.886	0.23919	5.2350	7.91
2022	19.8505	21.843	0.24487	5.3488	10.84
2023	20.2000	21.858	0.24847	5.4310	12.40
2030	26.8638	21.850	0.36329	7.9380	26.00

Appendix B. Battery capacity scenarios

To simulate future charging patterns, battery capacity distributions are estimated for the year 2030. Historical battery capacities from 2019 to 2022 are used to fit normal distributions, and trends in mean and standard deviation are extrapolated using linear and logarithmic regressions, respectively. These extrapolations define two future scenarios:

- 2030-H (high-growth): assumes continued rapid growth in battery capacity.
- 2030-L (low-growth): assumes growth slows due to saturation effects or cost constraints.

Fig. B.1 illustrates the empirical battery distributions and fitted normal curves. Table B.1 summarizes the extrapolated distribution parameters under each scenario.

Table B.1
Fitted means and standard deviations of battery capacity distribution, 2019–2030.

Year	EV Penetration (%)	Mean (kWh)	Std. Dev. (kWh)
2019	4.63	46.02	12.72
2020	6.55	49.48	13.85
2021	7.91	53.95	14.54
2022	10.84	55.47	15.46
2030-H	26.00	82.42	22.59
2030-L	26.00	69.36	19.04

Fig. B.2 presents the extrapolated trends in mean and standard deviation, while Fig. B.3 shows the resulting 2030 battery capacity distributions for both scenarios.

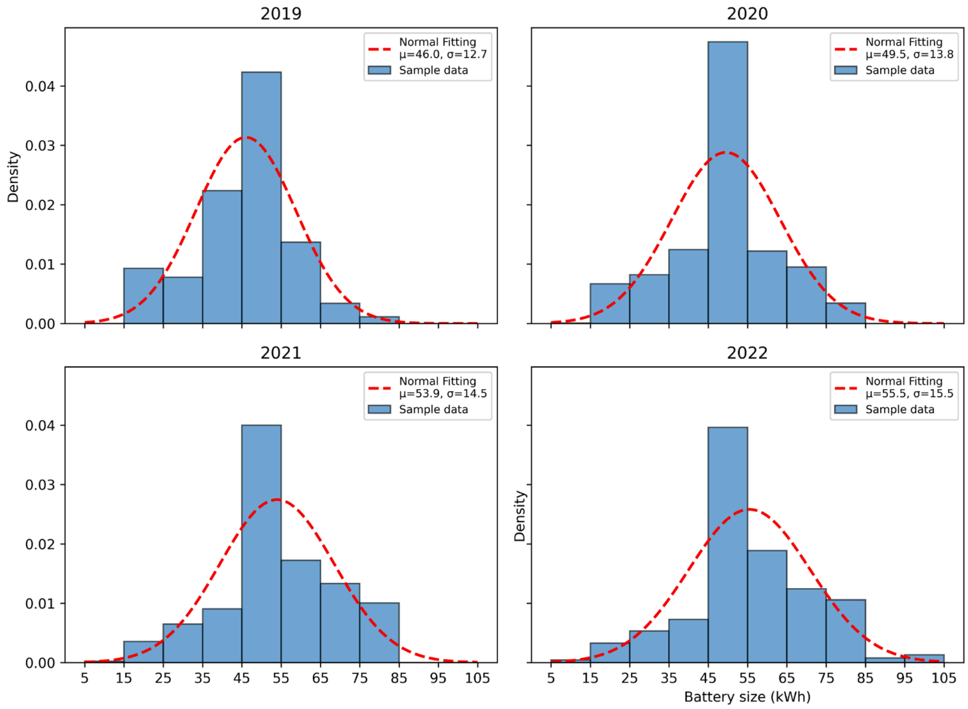

Fig. B.1. Battery capacity distribution and its normal fitting from 2019 to 2022.

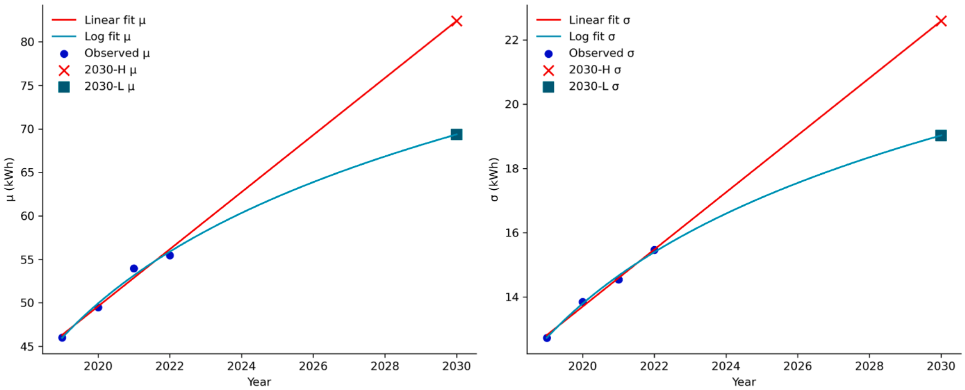

Fig. B.2. Extrapolated trends in battery capacity mean (left) and standard deviation (right).

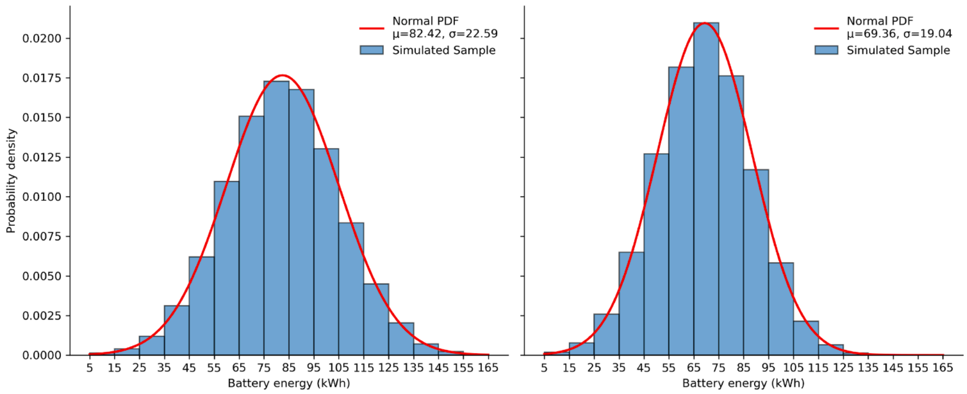

Fig. B.3. Projected 2030 battery capacity distributions under Scenario 2030-H (left) and Scenario 2030-L (right).

Table B.2 details the distribution of vehicles across battery capacity bins under each scenario. These values serve as inputs to the synthetic data generation process described in Section 3.3.

Table B.2
Share of vehicles by battery capacity bin under each scenario.

Battery capacity bin (kWh)	2021 (%)	2030-H high-growth (%)	2030-L low-growth (%)
5–15	0.23	0.11	0.18
15–25	3.56	0.40	0.80
25–35	6.51	1.22	2.52
35–45	9.07	3.23	6.43
45–55	40.00	6.34	12.64
55–65	17.24	10.88	18.47
65–75	13.34	14.92	20.67
75–85	10.05	17.63	17.85
85–95	0	16.53	11.51
95–105	0	12.86	5.85
105–115	0	8.35	2.28
115–125	0	4.52	0.64
125–135	0	2.00	0.14
135–145	0	0.74	0.02
145–155	0	0.22	0.01
155–165	0	0.06	0.00

Appendix C. Validation

The performance of the transformer-GMR framework, we conducted out-of-sample validation using a test set comprising weekly charging profiles from 9858 EVs, corresponding to approximately 4.25% of the full dataset. The model was applied to generate synthetic charging sequences for this held-out sample, which were then aggregated and compared to the actual observed profiles. Fig. C.1 illustrates the average weekly charging power curves for both the observed data and the model-generated sequences. The close alignment of the two curves visually confirms the model's ability to reproduce temporal patterns in charging behavior at the population level.

Quantitative evaluation further demonstrates the predictive accuracy of the model. The transformer-GMR framework achieves a Mean Absolute Percentage Error (MAPE) of 8.84%, a Root Mean Square Error (RMSE) of 265.22 kW, and an average daily Peak Error Percentage (PEP) of 3.34%. These metrics reflect the model's effectiveness in capturing both daily load shapes and peak demand, reinforcing its applicability for infrastructure planning and scenario-based forecasting.

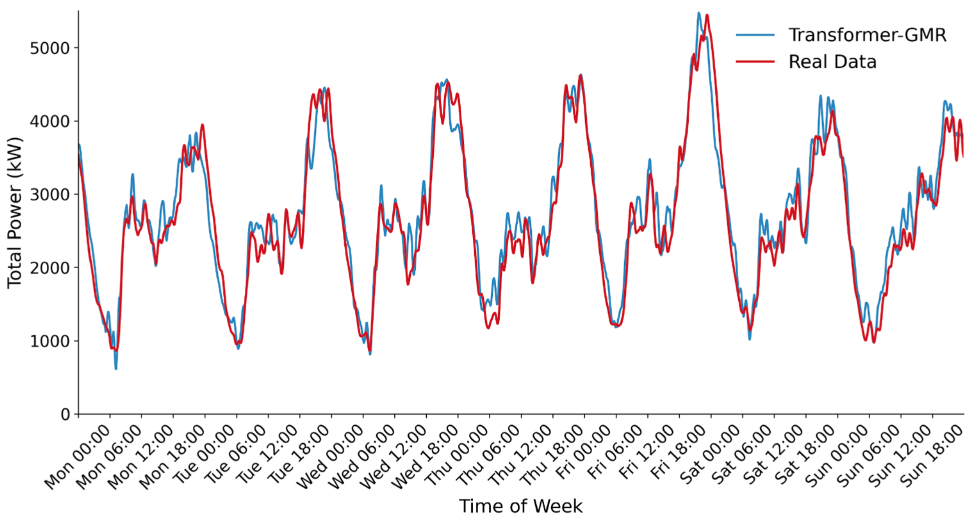

Fig. C.1. Comparison of observed and simulated average weekly charging power profiles (test set).

At the individual-event level, we further assessed the fidelity of the synthetic sequences by comparing the empirical distributions of charging duration and charged energy between the transformer-GMR outputs and the real data. Fig. C.2 presents overlaid density histograms for both metrics, and two-sample Kolmogorov–Smirnov tests yield p-values of 0.1517 for charging duration and 0.1292 for charged energy-both well above the 0.05 significance threshold. These results indicate no statistically significant difference between

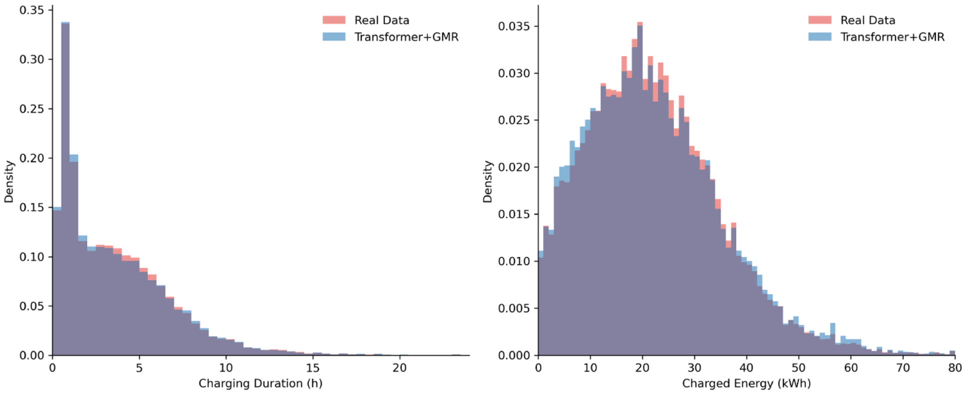

Fig. C.2. Empirical distribution comparison of charging duration (left) and charged energy (right) between real data and transformer-GMR synthetic outputs.

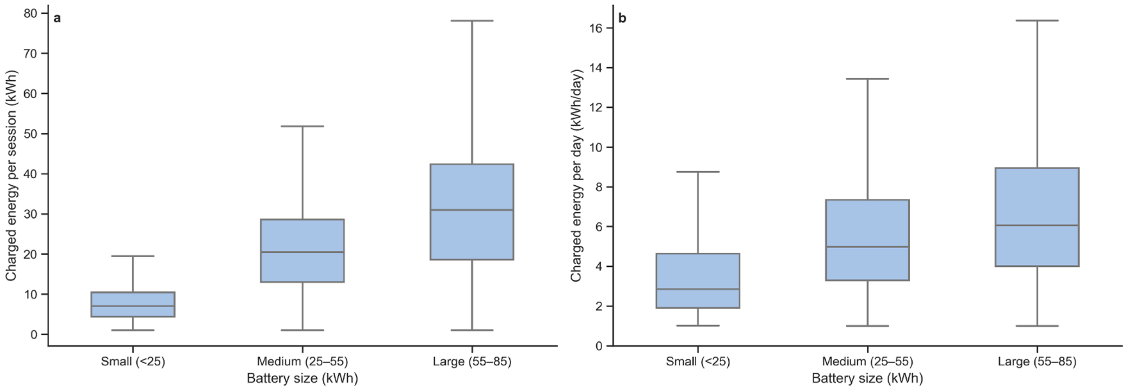

Fig. C.3. Distribution of charged energy per session (a) and per day (b) by battery capacity group in 2021.

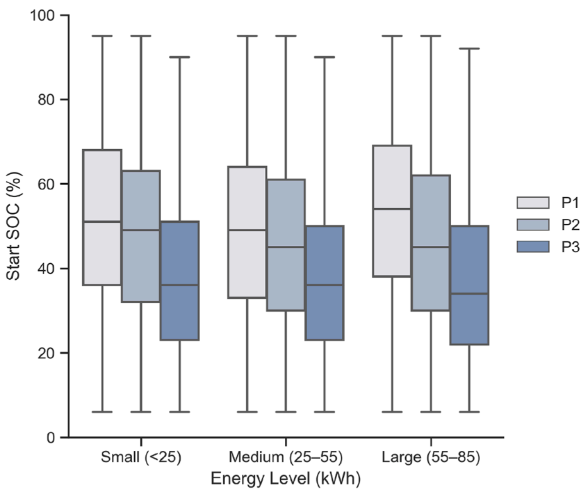

Fig. C.4. Empirical charging initial SOC by charger level by battery capacity group in 2021.

the generated and observed distributions, confirming that the transformer-GMR framework accurately reproduces not only aggregate temporal patterns but also the finer characteristics of individual charging events.

Appendix D. Statistical tests on initial SOC

To evaluate the two claims in the main text that higher charging power is generally initiated at lower initial SOC (SOC_0), and that within each charger level, the SOC_0 distributions differ across battery capacity groups, we conducted statistical tests. We first performed a two-way ANOVA with interaction, $initial\_SOC \sim C(battery\_size) \times C(power\_level)$, as an overall screen. The model indicated significant main effects of battery size and power level and a significant interaction (all $p < 0.001$), consistent with systematic differences in SOC_0 across battery groups and with those differences depending on charger level. Guided by this, we conducted within-level post hoc comparisons to localize contrasts: at P1 and P2, most pairwise differences between battery groups were significant, whereas at P3, several pairs were not, suggesting that initiation of high power charging is more uniformly concentrated at lower SOC across battery sizes (around 36% for Small–Large battery sizes and slightly above 40% for Premium group).

Because the validity of classical ANOVA and Tukey HSD relies on normal residuals and homogeneous variances, we then diagnosed the assumptions. Levene's test rejected homoscedasticity ($p \approx 0$), implying that parametric p values may be optimistic. Accordingly, we treated the ANOVA and post hoc results as supportive and diagnostic and based confirmatory inference on distribution-free tests aligned with these diagnostics.

Within each charger level we applied the Kruskal Wallis test to compare SOC_0 distributions across battery capacity groups; results were highly significant in all cases (P3: $p < 0.001$; P2: $p < 0.001$; P1: $p < 0.001$), confirming that battery size influences charging behavior regardless of charger type. Patterns in the within-level contrasts mirror the parametric screening: the clearest between-group separations occur at low and medium power P1 and P2, while differences attenuate at high power P3.

Overall, these test results suggest that higher charging power is generally preceded by lower SOC_0, and within each charger level, SOC_0 distributions differ significantly among battery capacity groups, with the strongest separation at P1 and P2 and weaker contrasts at P3.

Appendix E. A counterfactual scenario of 2030: no battery capacity increase

Fig. E.1 presents projected charging activity under the two 2030 scenarios alongside a counterfactual case that isolates the effect of battery capacity growth. The counterfactual (red curve) applies the 2030 vehicle stock to the 2021 battery capacity distribution, holding fleet size constant through 2030 while removing the shift toward larger batteries.

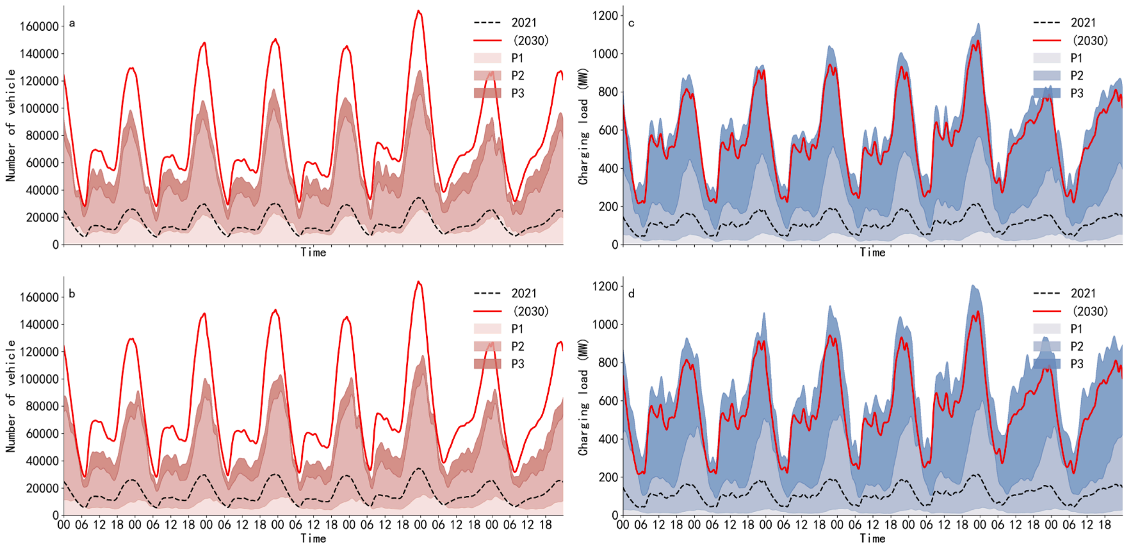

Fig. E.1. Projected charging activity under 2030 scenarios, with a contrast against a counterfactual 2030 case: (a) charging events – Scenario 2030-L, (b) charging events – Scenario 2030-H, (c) charging load – Scenario 2030-L, (d) charging load – Scenario 2030-H. Dashed lines represent 2021 baseline values for comparison. The red curve represents the counterfactual scenario in which the 2021 battery distribution is applied to the 2030 fleet size. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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