Privacy-Preserving Electric Vehicles Charging Simulation via Large-Language-Model-Guided Context-to-Behavior Probabilistic Synthesis

Hongyi Chen, Ziming Yan, Zhenyuan Du, Yan Xu
School of Electrical and Electronic Engineering
Nanyang Technological University
639798, Singapore
hongyi002@e.ntu.edu.sg, ziming.yan@ntu.edu.sg, e220188@e.ntu.edu.sg, xuyan@ntu.edu.sg

***Abstract*—The scarcity of privacy-preserving data has been a challenge in simulating and forecasting electric vehicle (EV) charging demand. This paper proposes a probabilistic synthesis framework for privacy-preserving simulation of EVs charging demand in distribution networks. The framework integrates a Large Language Model (LLM) context interpreter with a Hierarchical Generative Filter (HGF) in a configurable two-stage Monte Carlo Simulation (MCS) engine. The contextual factors (e.g., weather, calendar effects, events, and infrastructure status) are interpreted by the LLM into behavioral likelihoods through an HGF layer that calibrates simulation of charging arrivals, state-of-charge evolution, and queue-constrained charging services. In the two-stage MCS engine, the first stage samples context-conditioned behavioral profiles for individual EVs, and the second stage propagates the HGF-based SoC and charging decisions to obtain network-level demand distributions with quantified uncertainty. By projecting charging with synthetic samples rather than privacy-invading user traces, the proposed framework eases data scarcity and meets privacy rules while preserving operational realism. Simulation results show that the proposed LLM–HGF–MCS framework reproduces real-world variability in EV charging behavior, offering a scalable and privacy-compliant solution for intelligent charging demand forecasting.**

***Index Terms*—EVs charging demand, Large language model (LLM), Monte Carlo simulation, Event and scenario interpretation.**

I. Introduction

The rapid global adoption of electric vehicles (EVs) presents new challenges in reasonably forecasting charging demand, which is shaped by contextual and behavioral factors. Accurate forecasting of charging demands is essential for efficient planning and management of urban charging infrastructure [1]. However, cities experiencing accelerated EV adoption often face severe data limitations—including privacy regulations, incomplete records, and fragmented datasets—that undermine the reliability of conventional forecasting approaches [2], [3]. Moreover, EV charging behavior is strongly influenced by contextual factors such as weather, time of day, and social events, which traditional models struggle to capture effectively [4], [5]. For instance, adverse weather may suppress travel and charging activity, queuing may delay charging decisions, while favorable conditions may stimulate charging demands. These complexities highlight the need for a context-aware and privacy-preserving framework capable of addressing data scarcity while adapting to dynamic conditions.

Traditional data-driven forecasting models rely heavily on fine-grained historical data, which are often inaccessible due to privacy and collection inconsistencies [6], [7]. Although deep learning, spatiotemporal, and probabilistic approaches have improved short-term forecasting accuracy [8], [9], they remain limited in adaptability and often fail to capture behavioral or policy-driven incentives. Mid- and long-term models that classify EVs by type (e.g., private, taxi, fleet) [10], [11] lack responsiveness to real-time contextual variations, while hybrid and demographic models [12], [13] enhance interpretability but overlook incentive-driven variability and privacy issues [14], [15]. Consequently, existing forecasting paradigms face inherent challenges in scalability, reliability, and confidentiality. Addressing these limitations requires models capable of integrating heterogeneous contextual information while maintaining theoretical consistency.

Recently, Large Language Models (LLMs) have shown strong potential in linking semantic understanding with domain-specific reasoning in power and energy systems. Prior work has demonstrated LLM-assisted simulation workflows and decision tools for distributed energy resources [16], [17], while reinforced LLM frameworks have improved safety and adaptability in energy management [18]. These advances confirm that integrating LLMs with physics-based models could enhance interpretability and scalability under data-limited conditions. However, their application to EV charging demand forecasting remains largely unexplored, especially for probabilistic and privacy-sensitive settings.

Building on these advances, this paper proposes a probabilistic EV charging demand simulation framework that integrates an LLM context interpreter with a Hierarchical Generative Filter (HGF) layer in a Monte Carlo Simulation (MCS) engine. The LLM–HGF–MCS framework generates privacy-preserving synthetic datasets, captures stochastic behavioral responses to contextual variations without invading user trace privacy.

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II. Proposed Method

A. Framework of Proposed Method

This paper introduces a probabilistic EV charging demand framework that employs LLMs to generate privacy-preserving synthetic datasets that reflect real-world charging behavior. Instead of relying on sensitive user traces, the LLM infers behavioral patterns from non-personal contextual factors, capturing complex dynamics while preserving privacy. As shown in Fig. 1, the framework comprises three components: semantic interpretation, generative modeling, and probabilistic aggregation.

B. Event and Scenario Interpretation by LLM

In the proposed framework, the LLM operator $\mathcal{G}_{\text{LLM}}$ and rule kernel $\mathcal{R}$ jointly transform multi-contextual signals $x(t)$ (i.e., $L_{\text{weather}}, L_{\text{event}}, L_{\text{HVAC}}, \Delta\omega$) into a structured behavioral likelihood vector $\boldsymbol{\ell}(t)$, perturbed by Gaussian noise:

$$\boldsymbol{\ell}(t) = \mathcal{G}_{\text{LLM}}(\mathbf{x}(t);\theta) + \mathcal{R}(\mathbf{x}(t)) + \mathbf{n}(t), \quad \mathbf{n}(t) \sim \mathcal{N}(\mathbf{0}, \Sigma_\ell) \tag{1}$$

where, $\mathcal{G}_{\text{LLM}}$ compresses natural language contexts into quantitative behavioral cues, while $\mathcal{R}$ represents interpretable rule-based corrections (e.g., distance decay, activity intensity, and zone weighting). The residual term $\mathbf{n}(t)$ captures unexplainable stochastic effects, and Σ_ℓ is covariance of $\mathbf{n}(t)$.

The behavioral mapping operator then converts behavioral likelihood $\boldsymbol{\ell}(t)$ into hourly travel intensity $\lambda_h(t)$ and trip-type probabilities $\boldsymbol{\omega}(t)$:

$$\begin{aligned}
\lambda_h(cp,t) =& \lambda_h^{\text{data}}(cp)\,\exp\!\big(\theta_0 + \theta_h \tfrac{h}{24} + c^\top \ell(t)\big), \\
\tilde{\omega}(t) =& \omega_0 + B\,\Delta\omega(t), \\
\omega(t) =& \Pi_\Delta\big(\tilde{\omega}(t)\big).
\end{aligned} \tag{2}$$

where, $\lambda_h^{\text{data}}(cp)$ is the empirical hourly arrival rate at car park cp, derived from historical records and used to form the minute-level arrival profile (in this paper, collected from Singapore LTA API). The exponential term in $\lambda_h(cp,t)$ provides an LLM-driven modification around this baseline through a global offset θ_0, a time-of-day coefficient $\theta_h h/24$, and the contextual vector $\ell(t)$ (weather, events, HVAC load, etc.). The trip-type probabilities $\omega(t)$ are obtained by adjusting the baseline distribution ω_0 with the LLM-generated offset $\Delta\omega(t)$, transformed by the projection matrix B, and subsequently normalized onto the probability change Δ.

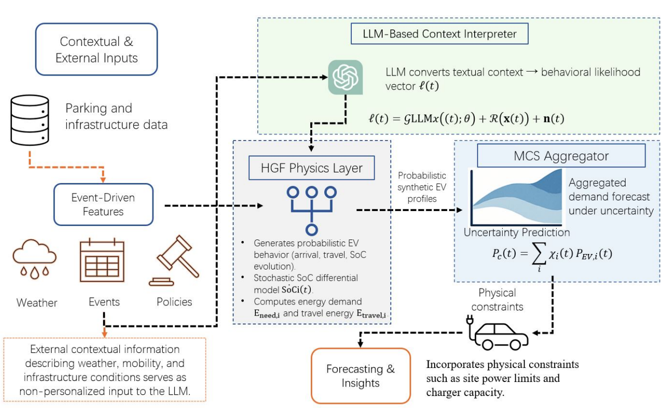

Fig. 1. The Framework of Proposed Method

The LLM maps free-text descriptions of events into a compact behavioral prior for the EV demand model. The system prompt for the LLM specifies four outputs: a normalized weather impact score $L_{\text{weather\_impact}} \in [-1,1]$, an event impact score $L_{\text{event\_impact}} \in [-1,1]$, an HVAC energy term $L_{\text{hvac\_load}}$ in kWh/km (typically 0–0.03), and a three-dimensional shift vector $\boldsymbol{\omega}_{\text{shift}}$ over commute, errand, and long-distance trips, all returned in strict JSON format. The user prompt injects the textual context into this template and reiterates the required keys, while a JSON schema validator constrains the response.

C. Stochastic SoC Modeling with HGF Layer

To generate context-aware charging demand profiles without relying on historical user-tracing data, a *Hierarchical Generative Filter* (HGF) layer is introduced. The HGF layer hierarchically composes context-to-behavior, behavior-to-SoC, and SoC-to-charging mappings, and filters LLM-proposed behavioral scenarios through physical charging SoC constraints to retain only feasible charging trajectories. The resulting SoC distribution is derived from travel-distance statistics [19], while its evolution follows an energy-balance formulation within the hierarchical generative layer:

$$\dot{\text{SoC}}i(t) = -\frac{\eta_d}{B_i} v_i(t) + \eta_c u_i(t) + \zeta_i(t), \quad \zeta_i(t) \sim \mathcal{N}(0, \sigma\zeta^2) \tag{3}$$

where, $\text{SoC}_i(t)$ is state-of-charge of EV i, η_d, η_c is discharge/charge efficiency, B_i is the battery capacity of EV i, $v_i(t)$ is driving power equivalent (consumption rate), $u_i(t)$ is charging power control signal, and $\zeta_i(t)$ is the process noise.

EVs trigger its charging decision when $\text{SoC}_i(t) < \text{SoC}_{\text{tar}}$ and parking duration is within threshold θ_p (set as 30 minutes in this paper). The required charging energy is expressed as:

$$E_{\text{need},i} = B_i[\text{SoC}_{\text{tar}} - \text{SoC}i(t_{\text{arr}})]_+, \quad \text{SoC}_{\text{tar}} \in [0.85, 0.95] \tag{4}$$

To determine total energy consumption $E_{\text{travel},i}$, driving efficiency e_{base} and HVAC load L_{HVAC} are integrated along the traveled distance:

$$\begin{aligned}
E_{\text{travel},i} &= \int_0^{T_i} e_{\text{km}}\big(h(t), L_{\text{HVAC}}(t)\big), \mathrm{d}d_i(t), \\
e_{\text{km}} &= e_{\text{base}} + L_{\text{HVAC}}
\end{aligned} \tag{5}$$

where $[x]_+$ is the positive-part operator $\max(x,0)$, e_{km} is the HVAC-adjusted energy-per-km, e_{base} the baseline consumption, $L_{\text{HVAC}}(t)$ the climate-dependent HVAC load, T_i the trip duration, and $d_i(t)$ the distance trajectory. Eq. 5 couples driving conditions, climate load, and energy use, with total consumption accumulated from both traction and HVAC components along the traveled distance. This constraint feeds into Eq. 3–4, forming a hierarchical LLM–rule-driven mechanism that maps contextual signals to charging-relevant energy states. The HGF therefore enables context-aware, physically consistent, and privacy-preserving synthesis of arrival SoC profiles for downstream queueing and demand optimization.

D. Queue-Constrained Aggregation with Monte Carlo Simulation

After deriving anonymized probability distributions of EV behaviors, a Monte Carlo Simulation (MCS) engine is developed to quantify expected charging demands and corresponding uncertainties. As shown in Fig. 2, the MCS operates in two steps: (i) sampling individual charging sessions to obtain aggregate power, and (ii) resampling probabilistic power trajectories from the resulting distribution.

LLMs convert non-personal contextual information into behavioral likelihoods for EV arrivals, parking durations, and charging needs. These statistical insights guide stochastic sampling within MCS to generate aggregated, privacy-preserving demand profiles. By iterating across diverse scenarios, the framework captures regional variations and event-driven responses, producing robust probabilistic load estimates under a privacy-by-design paradigm.

For a car park, the total electric vehicle (EV) charging load $P_c(t)$, is computed by summing all active charging sessions $\chi_i(t)$ as shown in Eq. 6. In the simulation scenario, this corresponds to summing the instantaneous occupancy of all chargers multiplied by the rated power of a single charging point. Thus, the aggregate charging demand with power density at state $p(\omega, t)$ is given by:

$$P_c(t) = \int_\Omega p(\omega, t)\, d\mu(\omega) = \sum_i \chi_i(t) P_{\mathrm{EV},i}(t) \tag{6}$$

To estimate the aggregated load profile, multiple full-day (1440-minute) scenarios are generated following the proposed algorithm. Each arriving EV is assigned randomized parking duration, charging duration, and state-of-charge (SoC), capturing behavioral variability. The chargers are allocated sequentially, and each EV occupies a charger until its energy requirement is met.

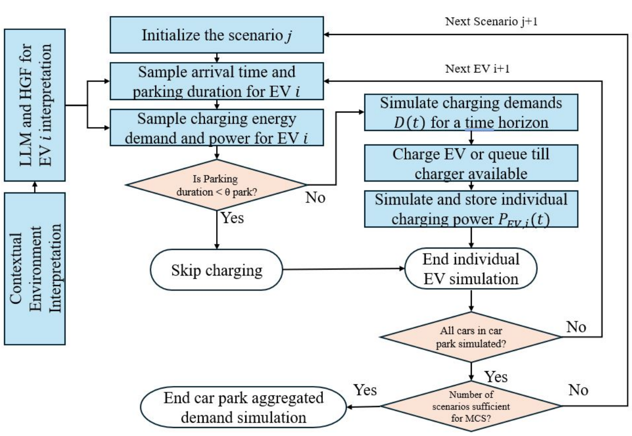

Fig. 2. Two-Stage Monte Carlo Simulation for Probabilistic Charging Power Predicting

Let $D^{(i)}(t)$ represent the charging demand in the i-th simulation scenario at time t. Based on the behavior interpretation in (1)-(5) and the aggregation of parking charging demand in (6) with the queuing model [19], the expected charging demand is calculated by averaging the simulation runs of N:

$$E[D(t)] = \frac{1}{N} \sum_{i=1}^{N} D^{(i)}(t) \tag{7}$$

where, N is the total number of simulation scenarios. This approach provides a more accurate estimation of average demand, particularly in cases where real-world data is insufficient or unavailable.

Additionally, the variance of the simulated demand scenarios can be computed as:

$$\mathrm{Var}[D(t)] = \frac{1}{N-1} \sum_{i=1}^{N} \left(D^{(i)}(t) - E[D(t)] \right)^2 \tag{8}$$

This variance quantifies the degree of uncertainty and spread in the demand predicts, helping to identify potential risk factors in EV charging infrastructure planning.

E. Simulated Chargers Utilization Rate

To evaluate the utilization rate of the charging infrastructure and amount of served energy in each car park, the car park level utilization rate is calculated:

$$\begin{aligned} E_{\text{day}} &= \int_0^{24h} P_c(t)\, dt \\ \text{Util} &= \frac{E_{\text{day}}}{24(C_f P_f + C_s P_s)} \end{aligned} \tag{9}$$

The daily energy E_{day} integrates power over 24 hours, while infrastructure utilization ratio Util normalizes it against total installed capacity, charger capacities (C_f, C_s) for fast and slow chargers.

Meanwhile, three indicators (load smoothness ($w_1 P_c^2$), uncertainty ($w_2\mathrm{Var}$), and utilization reward ($w_3\mathrm{Util}$)) are integrated into an unified performance metrics:

$$\mathcal{J} = \mathbb{E}_{t,\Omega}\Big[w_1 P_c^2(t) + w_2 \mathrm{Var}[D(t)] - w_3 \mathrm{Util} \Big] \tag{10}$$

where, w_1, w_2, w_3 are weight coefficients, $\mathbb{E}_{\Omega_m}[\cdot]$ is expectation over scenario-m.

III. Simulation Results

A. Scenario Analysis of Events and Weather Impact

Three real car parks in Singapore with occupancy patterns from Land Transport Authority datamall are leveraged to simulate EVs charging demands. Considering a scenario with five-day horizons, the weekend (Day 1–2) is forecasted to be with light rain, while weekdays (Day 3–5) is mostly sunny or cloudy. These conditions were processed by the LLM, which translated weather and event descriptors into modified arrival

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TABLE I
CHARGING DEMAND OF DIFFERENT SCENARIOS

Car Park	Scenarios and charging demand				
	Scenario	*Daily kWh*	*Peak kW*	*Avg Wait(min)*	*Utilization*
BM31	Weekday	3897.4	624	27.38	26.42%
	Weekend	3699	624	49.19	27.03%
PDJ3	Weekday	5340.4	624	17.385	36.98%
	Weekend	5003.4	624	17.39	33.30%
TPM	Weekday	3014	604.8	0	15.20%
	Weekend	3206.4	595.2	0	21.09%

and parking-duration likelihoods within the LLM–HGF–MCS framework.

Tab. I summarizes the scenario analysis results by synthetic MCS generation. The results reveal clear weather-induced behavioral shifts. At residential sites such as BM31, rainfall increases private-vehicle use, leading to higher weekend demand peaks and longer waiting times (27.38–49.19 min). PDJ3 shows a similar uplift due to weather-driven clustering, whereas peripheral sites like TPM remain largely unaffected, with stable load and negligible queuing. These findings demonstrate how contextual events could reshape mobility and charging patterns across regions and effect of LLM in providing weather-responsive forecasting. Consistently, the charging profile performance metrics $\mathcal{J}$ is simulated to be 28272.42 without event consideration, while simulated to be 24591.32 when LLM-based behavioral adjustments are included.

B. Analysis of Regional Charging Demand Variability

From a regional perspective, simulation results from three representative sites—SAM2, PDR2, and TPM—show pronounced spatial heterogeneity in EV charging demand under identical weather conditions. As illustrated in Fig. 3, SAM2, a remote residential area, exhibits clear morning and evening peaks dominated by commuter activity. In contrast, PDR2 and TPM, located in central or mixed-use zones, display stronger and more irregular fluctuations across the day. These discrepancies indicate that even regions with moderate baseline demand can experience highly volatile charging patterns driven by mobility variability, dynamic pricing, and contextual factors such as local events or weather disturbances.

Regional variations are further evident in the effect of EV penetration levels. Comparing Singapore's medium-term target of 50% with its long-term goal of 80% reveals how demand intensity and queuing behavior evolve across urban contexts. Fig. 4 compares day-average charging demand and queue length for BM31, PDJ3, and SAM2, showing nonlinear amplification in both load and congestion as penetration increases.

At BM31, a high-density residential site, average demand increases from 110.8 to 175.4 kW, with peak load reaching 624 kW at 80% penetration. Queue length grows sharply (Max Q=33; Avg Q=16.6), indicating near-capacity saturation. PDJ3 exhibits a dual-peak profile linked to morning arrivals and evening departures; under 80% penetration, peak and average demand rise to 624.0 and 238.0 kW, with moderate queuing (Max Q=4) driven by temporal clustering rather than

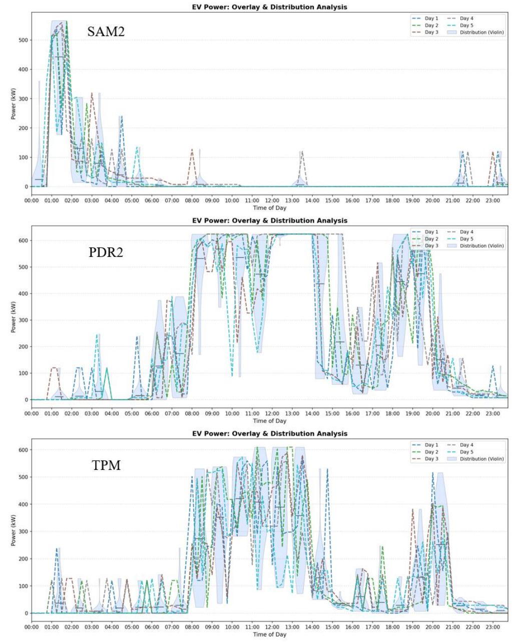

Fig. 3. Differences in EV Charging Demand between Regions

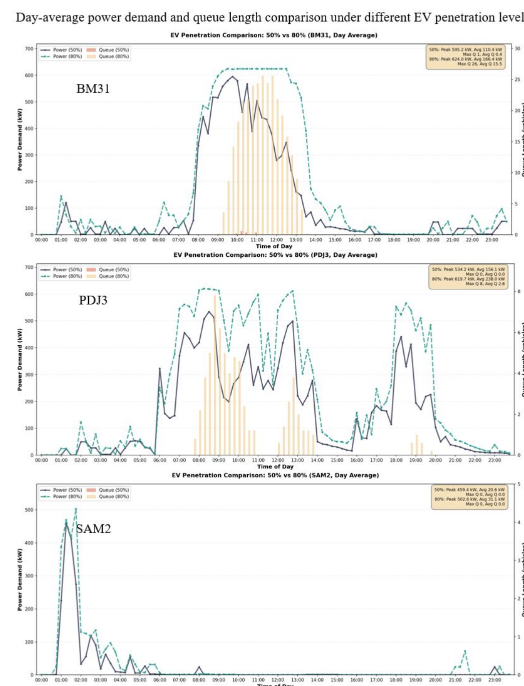

Fig. 4. Comparison of Day-Average EV Charging Power and Queue Length under Different Penetration Rates

capacity limits. By contrast, SAM2, a peripheral site, shows only modest load growth (21.8 to 31.4 kW) and negligible queuing, reflecting low and dispersed usage.

Overall, these results reveal distinct regional responses to EV adoption—capacity saturation in dense zones, behavioral variability in mixed-use areas, and stability in peripheral regions—emphasizing the need for context-aware, region-

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specific planning.

C. Investigate the Impact of LLM Interpretation

Fig. 5 compares a 24-hour probabilistic charging demand before and after integrating an event-driven LLM adjustment. In this experiment, a mid-day price-discount signal (introduced to reflect high PV availability) was provided as contextual input, and the LLM translated it into an increased likelihood of mid-day arrivals.

The LLM-adjusted mean (blue) preserves the overall trend but shows a clear temporal shift: the main peak moves from 09:00 (39 kW) to 12:00 (42 kW), indicating users delaying charging in response to the discount. This shift also reduces the evening peak due to redistributed load. The 5th–95th percentile bands further confirm this behavioral change. Morning uncertainty widens, capturing early-arrival variability, while evening uncertainty contracts due to reduced congestion.

Overall, the results show that embedding LLM-interpreted events—here, a PV-driven price incentive—directly reshapes both mean demand and uncertainty structure, enabling more realistic and context-responsive probabilistic load synthesis.

IV. Conclusions and Future Work

The proposed probabilistic EV charging demand simulation framework addresses the privacy constraints of conventional methods by leveraging LLMs to generate synthetic privacy-preserving datasets. The LLM interprets non-personal contextual factors such as weather and events into behavioral likelihoods, enabling realistic charging simulations without accessing sensitive user data. Combined with a Monte Carlo engine, the framework captures regional variability and stochastic fluctuations, reproducing short-term volatility and extreme demand events while maintaining operational realism.

Results demonstrate that the LLM–HGF–MCS framework provides representative simulation of EV charging demands across diverse conditions, providing insights for resilient and privacy-compliant infrastructure planning. Through synthetic data generation, the strict privacy protection is enabled by design. Future work will integrate the EV charging demand modeling in a planning optimization framework, and provide regional policy simulation to further enhance flexibility and generalization within complex EV ecosystems.

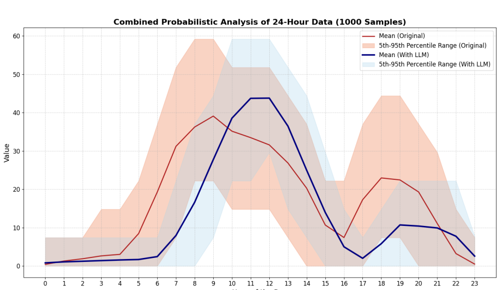

Fig. 5. Comparison of probabilistic analysis results with and without LLM-based contextual interpretation for a 24-hour charging demand.

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