Spatio-Temporal Modeling of Urban Electric Vehicle Charging Demand Incorporating Real-World Traffic Dynamics

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***Abstract*—The growing penetration of electric vehicles (EVs) creates new challenges for distribution systems and charging infrastructure. Uncoordinated charging can produce load spikes, voltage instability, and local congestion, while also increasing operational and financial risks for Charging Network Operators (CNOs) through uncertain real-time demand and higher procurement costs. Accurate forecasting of spatiotemporal charging demand is therefore essential for proactive grid management and reliable network operation. This paper presents a traffic-based simulation framework for generating realistic EV load profiles in urban environments. The model integrates real road network topology, population density, empirical arrival rates, and historical traffic data to capture congestion patterns and travel behavior. These EV mobility patterns are then supplied to a queuing-based charging model that estimates station-level performance, including served demand and aggregate power and energy requirements. By combining traffic simulation with queuing theory, the framework provides detailed insight into both local and citywide charging dynamics. The proposed approach offers a data-driven foundation for planning and operating future charging networks, supporting effective station siting, anticipation of peak demand periods, and the design of targeted demand-management strategies.**

***Index Terms*—Charging demand forecasting, Charging network operators, Electric Vehicle, Spatio-Temporal Modeling, Traffic simulation**

I. Introduction

Electric vehicle (EV) sales surpassed seventeen million units globally in 2024, representing more than twenty percent of total car sales and marking an increase of three and a half million over the previous year. China continues to lead the global EV market, with half of all car sales in 2024 being electric and one in ten vehicles on Chinese roads now powered by electricity. In the United States, EV sales also increased by ten percent [1]. The widespread adoption of EV's offers several advantages, including reduced dependence on fossil fuels, improved energy security, and mitigation of global warming impacts [2]. EV's can further support power system management through scheduled charging and discharging, power quality improvement, and voltage and frequency support.

Despite these benefits, high levels of EV penetration can introduce significant challenges [3]. Rapid growth in charging demand may increase load during peak hours, overload components, create phase and voltage imbalances, elevate harmonic distortion, increase power losses, and reduce overall grid stability [4]. These issues pose operational and economic challenges for Charging Network Operators (CNOs), who must manage uncertain demand profiles, plan day-ahead procurement, and remain exposed to volatile real-time market prices. Accurate modeling of EV charging demand is therefore essential for anticipating usage patterns, mitigating local grid stress, and enabling CNOs to adjust pricing strategies to maintain profitability [5], [6].

Forecasting EV charging demand remains difficult because charging behavior is highly stochastic and depends on diverse and unpredictable user patterns. Unscheduled or opportunistic charging can impose substantial stress on local distribution infrastructure as adoption rates continue to rise. As a result, there is a growing need for accurate frameworks capable of predicting EV load demand across regions with greater spatial and temporal resolution [7].

A broad range of studies has focused on forecasting EV charging demand and modeling its interaction with transportation and power systems. In [8], the authors construct a transportation network that incorporates both gasoline and electric vehicles, accounting for route selection, charging opportunities, electricity prices, and distribution system constraints. The model determines system equilibrium by jointly solving a traffic assignment problem and an optimal power flow problem. Similarly, the study in [9] develops separate transportation and power system models. The transportation model provides EV driving and charging decisions, while the power system model evaluates locational marginal prices. These models interact to achieve a coordinated equilibrium that minimizes overall system cost.

Several works focus on demand estimation using real charging data. In [10], historical data from an EV charging station are analyzed directly rather than relying on simulated traffic behavior. In [11], a spatially and temporally varying Poisson arrival rate is used to model EV arrivals at fast-charging stations, and dynamic pricing is applied to control charging demand. A spatial–temporal model for highway fast-charging stations is developed in [12], where EV arrival rates are estimated using a fluid dynamics approach and incorporated into a queuing formulation. In [13], real-time traffic and grid data are used to estimate charging durations, enabling drivers to navigate toward stations with shorter waiting times.

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Traffic-aware and data-driven approaches have also been widely explored. In [14], a framework is presented to identify optimal charging stations while minimizing both travel time and charging cost, combining real-time traffic conditions with power system loading and locational marginal prices. The work in [15] applies autoregressive integrated moving average (ARIMA) modeling to forecast total electric load, including EV demand derived from probabilistic driving and charging parameters and historical load data. In [16], traffic flow is forecast using a convolutional neural network model, followed by a mixture-based approximation of EV arrival rates and queuing-based modeling of charging behavior. Likewise, [17] evaluates machine-learning models such as Random Forest, Categorical Boosting, Extreme Gradient Boosting, and Light Gradient Boosting to forecast EV charging demand using historical station data processed into multiple time intervals.

Other studies incorporate stochastic user behavior and empirical data. In [18], a Markov chain approach is adopted to capture influences from traffic, user behavior, and weather variability. In [19], EV ownership is estimated using the Bass diffusion model, and empirical charging behavior is combined with Monte Carlo simulations to generate realistic future charging profiles. A pilot study in [20] collects GPS-enabled driving and charging data from more than one hundred EV participants and uses these data to forecast aggregate charging load.

Building on these studies, the present work develops a traffic simulation framework for the City of Austin to generate realistic, time-varying EV arrival rates at charging stations. By including real road network characteristics, congestion patterns, and travel dynamics to produce spatial and temporal estimates of charging demand across different regions of the city. These arrival rates are integrated into a queuing-based model to evaluate charging station performance, network-wide utilization, and aggregate EV load demand.

The remainder of this paper is organized as follows. The proposed methodology is developed in Section II. Data sources and the simulation parameters are described in Section III. Section IV examines the results and provides the accompanying analysis. Concluding remarks and directions for future work appear in Section V.

II. Proposed Methodology

This study integrates concepts from traffic flow theory, stochastic demand modeling, and queuing systems to construct a unified spatiotemporal representation of EV charging behavior in an urban transportation network.

Let $G = (V, E)$ denote the road network, where V is the set of nodes and E the set of edges. A citywide vehicular flow profile $V_{bg}(t)$ is treated as an exogenous, time-varying signal derived from empirical detector counts. To spatialize this aggregate flow across the network, a population-weighted allocation is applied. Each edge $e \in E$ is assigned a weight s_e proportional to the surrounding population density such that

$$\sum_{e \in E} s_e = 1. \tag{1}$$

The background traffic on each edge is then modeled as

$$v_e^{bg}(t) = s_e \, V_{bg}(t), \tag{2}$$

yielding a consistent distribution of congestion pressure that follows the population structure of the service region.

To capture congestion effects, the model computes travel times for each edge based on total vehicle flow. For a road segment e, the free-flow travel time is

$$t_{0,e} = \frac{L_e}{v_{ff,e}}, \tag{3}$$

where L_e is the segment length and $v_{ff,e}$ the free-flow speed. The total flow is the sum of background (non-EV) $v_e^{bg}(t)$ and EV-induced traffic $v_e^{ev}(t)$. Congestion effects are incorporated using the Bureau of Public Roads (BPR) volume–delay function [21]:

$$t_e(t) = t_{0,e} \left[1 + \alpha \left(\frac{v_e^{bg}(t) + v_e^{ev}(t)}{C_e} \right)^{\beta} \right] + \delta_e, \tag{4}$$

where α and β are calibrated parameters, C_e is edge capacity, and δ_e captures intersection control delay. This expression reflects the nonlinear rise in travel time as volume approaches capacity, enabling dynamic routing decisions in the simulation.

Next, EV arrivals at charging stations are generated through a non-homogeneous Poisson process (NHPP) using the thinning algorithm. The arrival rate is defined as

$$\lambda(t) = \max\left(\lambda_0 - A \sin\left(\frac{4\pi t}{T} \right), 0 \right), \tag{5}$$

where λ_0 is the baseline rate, A is the amplitude, and T is the period. The sinusoidal structure produces a pair of daily peaks that are similar to typical morning and evening weekday travel patterns.

Routing behavior is modeled by assuming each EV selects a charging station that minimizes a generalized travel cost,

$$C = t_{\text{travel}} + P_{\text{queue}}, \tag{6}$$

where t_{travel} is the congestion-dependent travel time from the BPR model and P_{queue} is a penalty proportional to the current station queue length. EVs choose routes based on shortest-path principles over a weighted graph whose edge weights dynamically vary with congestion. Whenever traffic levels shift enough to change the optimal path, the route is recalculated, producing a temporally evolving representation of driver adjustments.

Charging stations are modeled as multi-server queues, where the number of servers c corresponds to the number of available plugs. Arriving EVs begin charging immediately if a plug is available; otherwise, they join a first-come–first-served (FCFS) queue. The required energy is computed as

$$E_{\text{req}} = (1 - \text{SoC}) \, E_{\max}, \tag{7}$$

and charging duration is given by

$$t_{\text{service}} = \min\left(\frac{E_{\text{req}}}{P_{\text{stn}}} \times 3600, \ t_{\max} \right), \tag{8}$$

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where P_{stn} is the station's rated power and $t_{\max}$ is a practical upper bound on charging time. This yields an $M/G/c$ queue, with time-varying Poisson arrivals and service times determined by battery state, charging power, and the truncation limit. In the simulation, key parameters such as the BPR function and charging mechanism influence the magnitude and temporal distribution of charging demand without altering the overall structure of the demand patterns.

III. Simulation Setup

The simulation integrates real traffic measurements, an urban road network derived from geographic data, charging station characteristics, and population-based spatial weighting to generate realistic spatiotemporal EV charging demand across Austin, with parameter values drawn from established traffic-flow literature and publicly available transportation datasets. The setup involves (i) data acquisition and preprocessing for traffic, network, and population inputs, (ii) representation of network performance and congestion, and (iii) incorporation of EV demand generation and behavioral dynamics.

Citywide background vehicular flow $V_{bg}(t)$ was constructed from 15-minute detector volumes in the City of Austin radar traffic count dataset [22]. Faulty and negative entries were removed, and a continuous time variable was defined as

$$\text{time}_h = \text{Hour} + \frac{\text{Minute}}{60}. \tag{9}$$

Detector volumes were aggregated across all available sensors, converted to vehicles per hour, clipped between the first and ninety-ninth percentiles to reduce outliers, and interpolated to produce a smooth 96-point diurnal profile with 15-minute resolution.

The Austin road network was extracted from OpenStreetMap [23] and reduced to its largest connected subgraph. Charging station locations, plug counts, and power ratings from [24] were mapped to their nearest nodes in the network and aggregated into functional charging facilities. Population counts from the constrained WorldPop dataset [25] were sampled at network nodes to create origin weights for EV trip generation, while edge midpoints were sampled to assign the population-proportional coefficients s_e used in the spatial allocation of $V_{bg}(t)$ through (1). Nodes lacking population support or with unreachable charging options were removed to ensure consistent connectivity.

Network performance was computed for each directed edge $e = (u, v, k)$ using geometric and speed attributes from the OpenStreetMap dataset. Free-flow travel time was calculated using (3). When speed information was missing, a default value of 11.11 m/s (40 km/h) was assigned. Edge capacity C_e was estimated from lane counts and highway-type capacity per lane. Congested travel time was derived from the BPR formulation in (4) using $\alpha = 0.15$ and $\beta = 4.0$. Intersection delay δ_e was determined based on node degree and the road class associated with each link. Background flow $v_e^{bg}(t)$ was obtained from (2). EV flow was approximated as

$$v_e^{ev}(t) = n_e(t)\,\frac{3600}{\max(t_{0,e},\,2)}, \tag{10}$$

where $n_e(t)$ is the number of EVs on edge e at time t.

EV demand was generated using the stochastic arrival model introduced in (5), adopting $\lambda_0 = 60$ veh/h and $A = 60$ veh/h. Each EV selected an origin node from the population-weighted distribution and then evaluated its five nearest charging stations, choosing the facility that minimized the generalized cost in (6). In this expression, t_{travel} represents the congestion-dependent travel time computed from the BPR model, while the penalty P_{queue} reflects queue length and is capped at 900 seconds.

Dynamic re-routing was triggered every four edges or when predicted travel time exceeded twice the free-flow value $2t_{0,e}$. Shortest paths were computed using Dijkstra's algorithm [7] with edge weights updated online according to congestion. Upon arrival at a charging station, EVs interacted with a FCFS queue modeled using a SimPy resource with service capacity equal to the number of available plugs.

Arrival state-of-charge (SoC) was drawn from a truncated normal distribution,

$$\text{SoC} \sim \mathcal{N}(0.3,\,0.1), \qquad 0.05 \le \text{SoC} \le 0.95. \tag{11}$$

Required energy was computed using (7) and charged at station's rated power $P_{\text{stn}} \ge 0.5$ kW. The charging duration followed (8) with a maximum allowable duration of $t_{\max} = 45$ minutes. This produced time-varying service rates within an $M/G/c$ queueing structure, consistent with realistic urban charging dynamics.

IV. Results

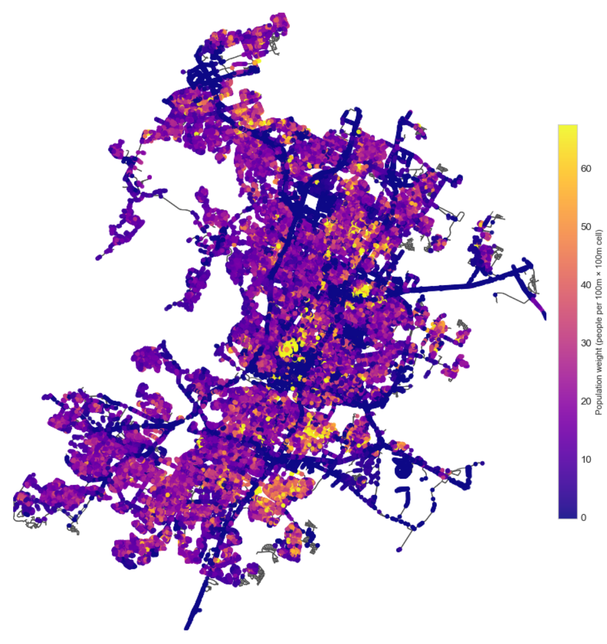

Fig. 1. *Population weighted road map of Austin.*

A population-weighted visualization of the Austin road network is presented in Fig. 1, where darker shading indicates segments that serve denser neighborhoods. This weighting forms the basis for distributing background traffic and EV trip

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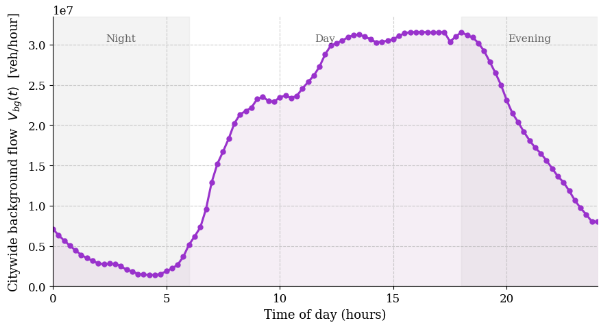

Fig. 2. *Background traffic flow in the city of Austin.*

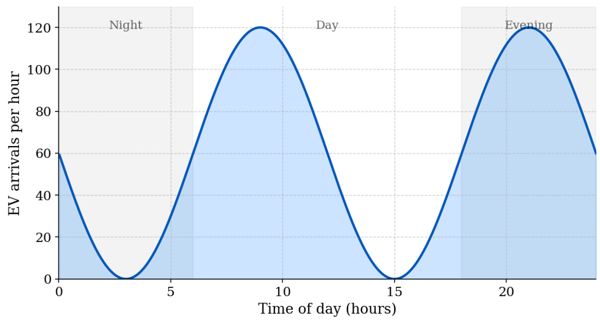

Fig. 3. *EV arrival rate for a 24 hour period.*

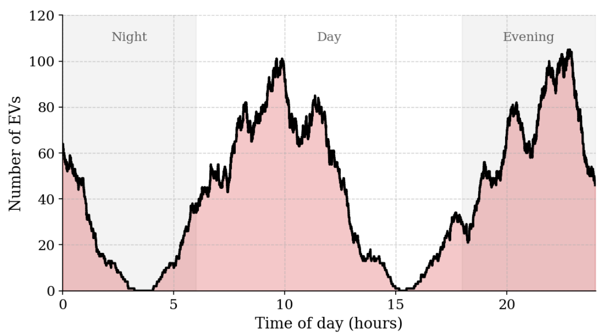

Fig. 4. *Number of EV charging across the 24 hour period.*

origins throughout the region. The daily pattern of background traffic, shown in Fig. 2, reflects typical metropolitan mobility. Volumes begin rising shortly before sunrise, peak during the morning commute, and remain elevated until early evening before tapering toward nighttime lows. The EV arrival rate used for the simulation exhibits a similar temporal structure. As illustrated in Fig. 3, arrival intensity reaches two peaks aligned with morning and evening rush hours, consistent with the sinusoidal rate function commonly used in customer arrival [26].

Charging activity across the full network mirrors these arrival trends. Throughout the day, the number of EVs actively charging follows the same two-peak pattern, with a total of 1,425 EVs spawned during the simulation. Fig. 4 displays this temporal profile. Spatial patterns also emerge when examining station utilization. Fig. 5 highlights how charging activity varies across the city. Of the 1,425 EVs generated, 1,382 completed a charging session, with the remaining vehicles still

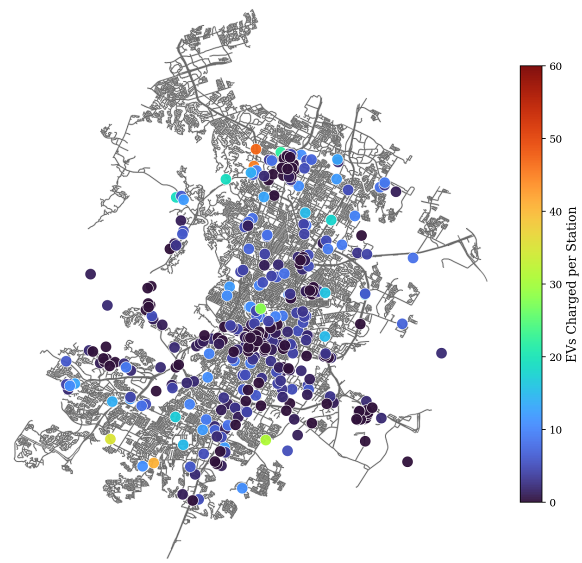

Fig. 5. *Charging station utilization across the Austin City.*

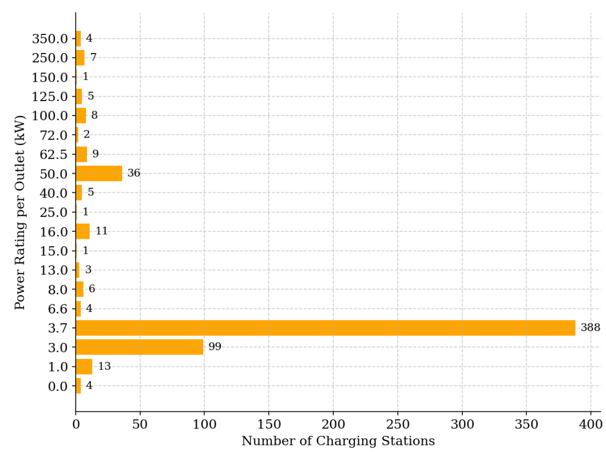

Fig. 6. *Distribution of EV charging stations by power rating.*

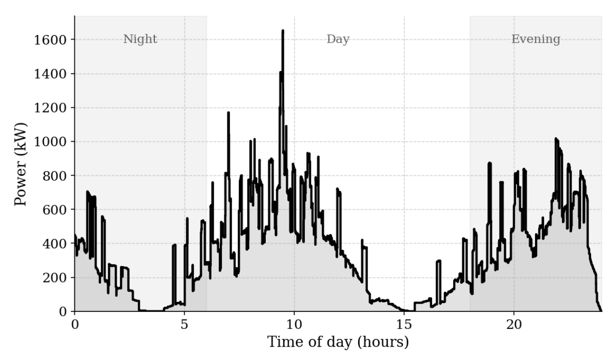

Fig. 7. *Demand from the charging station.*

in service when the simulation concluded. The busiest station served 47 EVs, indicating substantial heterogeneity in how demand is distributed geographically.

The distribution of power ratings among the charging stations provides context for these utilization differences. As

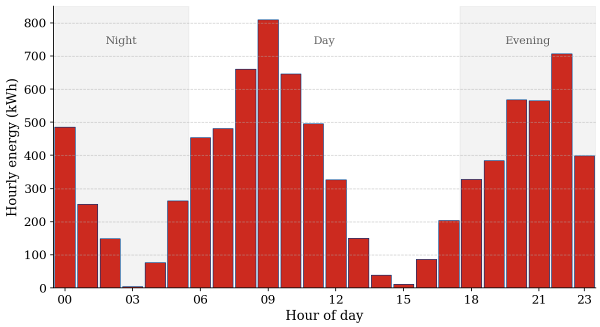

Fig. 8. *Energy demand from the charging station.*

shown in Fig. 6, most stations offer 3.7 kW charging, indicating that Level 2 infrastructure dominates the local landscape. The aggregate power drawn from all stations throughout the day is depicted in Fig. 7. Energy consumption, computed cumulatively, appears in Fig. 8. Both curves follow the diurnal arrival pattern, with the highest power and energy usage aligned with morning and evening peaks. Across the 24-hour period, the cumulative energy drawn from the charging infrastructure reaches approximately 8.588 MWh.

V. Conclusions and Future Work

This study presents a framework for forecasting urban EV charging demand by integrating key spatial and temporal determinants of charging behavior. Through the combination of empirical traffic data, spatially distributed charging stations, and probabilistic arrival processes, the model captures how EVs interact with both the transportation network and the charging ecosystem across the day. The model's outputs can be directly used to evaluate the siting of new charging stations by identifying high-traffic regions and persistently congested locations, as well as to assess congestion risk.

Future work will incorporate pricing as an additional driver of charging choice. With further addition of a distribution network and real-time and day-ahead electricity market models, the framework can be extended to evaluate advanced demand-side management strategies, enabling charging network operators to assess the impacts of dynamic pricing, congestion-aware incentives, and coordinated charging on operational performance and grid conditions.

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