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ARTICLE

Simulation-Based Feasibility Assessment of Electric Vehicle Charging Stations in Public Facilities

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ABSTRACT: The expansion of public electric vehicle (EV) charging infrastructure requires facility-level planning methods that account for uncertain vehicle arrivals, charger availability, queueing behavior, electrical demand, and tariff-based operating cost. This study presents a simulation-based decision support framework for estimating the feasibility of installing Electric Vehicle Supply Equipment (EVSE) in public facilities. The method integrates a Monte Carlo arrival model with a discrete-event charging simulation and a demand-sensitive cost model. Daily EV arrivals are generated using weather severity and calendar-based demand factors, split by vehicle type, and converted into hourly annual arrival schedules. The discrete-event model routes vehicles to compatible chargers, represents charger occupancy, waiting, charging delay, release, vehicle departure without charging, and records service and utilization statistics. The resulting charging-event and hourly-utilization data are then used to estimate energy consumption, monthly peak demand, energy charges, demand charges, and total operating cost. A representative facility case is used to evaluate weather-severity sensitivity and charging-station configuration sensitivity. Results show that monthly demand peaks and operating costs are sensitive not only to the number and power rating of chargers but also to the coincidence between EVSE charging activity and existing facility load. The framework supports preliminary EVSE planning by allowing public facility managers to compare charger-count scenarios, estimate utility-bill impacts, and identify months with elevated peak-demand risk before investment decisions are finalized.

KEYWORDS: Electric vehicle charging; EVSE; public facilities; Monte Carlo simulation; discrete-event simulation; demand charges; energy cost; charging infrastructure planning

1 Introduction

The transportation sector remains a major target for energy decarbonization because it contributes a large fraction of greenhouse gas emissions and depends heavily on petroleum fuels [1]. Battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), collectively referred to as electric vehicles (EVs), can reduce tailpipe emissions and petroleum dependence; however, their adoption depends strongly on convenient, reliable, and adequately distributed charging infrastructure [2,3].

Public charging infrastructure is especially important for users who lack home charging, for long-distance travel, and for public facilities that attract visitors over extended dwell times. Public facilities such as parks, campuses, government complexes, and recreational areas must evaluate not only whether charging stations are socially desirable but also whether their operational energy and demand costs are manageable [3–5]. Recent studies also emphasize public-charging service provision and the reliability and resilience of installed charging infrastructure [6–8].

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A central challenge is that EVSE feasibility is not determined by annual energy consumption alone. Commercial electricity tariffs often include demand charges based on the maximum power draw during a billing period. Even if total EV charging energy is moderate, simultaneous charging events can increase monthly peak demand and raise utility costs. Facility-level EVSE planning therefore requires a model that represents uncertain vehicle arrivals, charger availability, queueing, charging duration, power rating, and utility rate structure [9].

The objectives are to: (i) generate stochastic EV arrival profiles using weather and calendar factors; (ii) simulate charger allocation, queueing, and charging events using a discrete-event model; (iii) estimate monthly energy consumption, peak demand, and operating cost; and (iv) evaluate sensitivity to weather severity and charger configuration. The primary contribution of this study is the integration of stochastic EV arrival generation, discrete-event charging simulation, and electricity-cost estimation within a unified facility-level feasibility-assessment framework. Although these individual modeling components are well established, their integration enables uncertain EV arrival behavior to be translated into operational and economic performance measures, including charger utilization, charging-service performance, energy consumption, peak demand, and operating cost. By linking demand variability, charging operations, and utility costs within a common workflow, the framework provides facility managers with an actionable decision-support approach for evaluating alternative EV charging-station configurations and infrastructure-planning scenarios.

2 Literature Review

2.1 EV Adoption, Emissions, and the Need for Public Charging

Transportation electrification continues to be promoted as a pathway for reducing petroleum dependence and transportation-related greenhouse gas emissions. Current national and international assessments show that EV deployment is increasing rapidly, and public chargers have expanded substantially in recent years [1–3]. However, charging availability remains uneven across locations and user groups. This point is important for public facilities because visitors may not have access to home charging, may arrive from outside the local area, and may require charging during long dwell-time activities such as recreation, campus visits, or public services [3,5].

EVSE planning for public facilities is motivated by three connected concerns: reducing transportation-related emissions, improving access to public charging, and forecasting when vehicles arrive, wait, charge, or leave rather than estimating only aggregate annual energy. The supporting literature points to specific parts of this problem: public-charging service models and policy context [6], charger reliability and resilience [7,8], global charging-infrastructure and sustainable-energy solution reviews [10], national coverage gaps and equitable access [11,12], optimization of charging infrastructure [13], and uncertainty-aware siting, sizing, and upgrade decisions [9,14].

2.2 Lack of Adequate Charging Infrastructure as a Continuing Barrier

Early consumer-adoption studies identified limited range, high vehicle cost, and inadequate charging infrastructure as major barriers to widespread EV adoption [15]. Later cross-national work also found that charging infrastructure availability is statistically associated with EV market share, alongside financial incentives and other country-level factors [16]. These findings support the premise of this study: public EVSE can reduce range and access concerns only when chargers are available at suitable locations and can serve arriving vehicles with acceptable waiting or loss-of-service outcomes.

Recent evidence reinforces the same point at a larger scale. The International Energy Agency (IEA) reports that public chargers have grown rapidly but emphasizes that access to public charging is still needed for mass adoption, especially for users without reliable home charging [3]. Planning studies by the National Renewable Energy Laboratory (NREL) further show that future EV charging requirements depend strongly on vehicle adoption, travel behavior, charger type, and the spatial distribution of demand [4,5]. Therefore, public facilities cannot assume that installing a small number of chargers will automatically satisfy future demand; instead, they need demand-aware planning tools that estimate how many vehicles may arrive, when they arrive, and whether compatible chargers are available.

2.3 Public Charging Infrastructure as a Facility-Level Planning Problem

Public charging infrastructure is often evaluated at the national, regional, or corridor scale. These studies are valuable because they identify broad gaps in charging coverage, prioritize interstate and urban charging corridors, and estimate infrastructure requirements under future EV adoption scenarios [4,5,11]. However, a facility manager faces a more local decision: how many chargers should be installed at a specific site, what charger types are appropriate, how many users will be served, and how the additional load will affect the facility utility bill.

Earlier modeling studies addressed public-charging infrastructure location and stochastic EV/PHEV charging demand [17,18]. Recent reviews of charging infrastructure planning show that electric vehicle charging station (EVCS) planning involves both siting and sizing decisions, uncertainty in demand, grid upgrade requirements, and the need to coordinate charger deployment with local distribution-system capacity [9,13,14]. These concerns are directly related to the present study. A public facility may have sufficient annual energy capacity to support charging, but still experience higher monthly peak demand if multiple vehicles charge at the same time. Thus, the facility-level problem is not only where to place chargers, but also how charging events interact with existing building demand and commercial electricity tariffs. Building-level charging studies also show that EVSE can materially increase site peak demand and electricity bills, especially when chargers are located behind the same meter as the host facility [19,20]. Electricity-rate studies further demonstrate that tariff design, station utilization, and demand charges can strongly affect charging-station operating cost [21,22].

2.4 Policy Incentives, Equity, and Reliability of Public Charging

Policy incentives and charging availability have historically played important roles in EV adoption. Earlier literature showed that financial incentives and charging infrastructure were significant predictors of EV adoption across multiple countries [16]. Incentives remain relevant, but current EVSE research increasingly emphasizes whether public chargers are reliable, accessible, and usable when drivers arrive. Reliability and resilience studies show that installed charger counts alone can overstate effective charging access [7,8], while recent national analyses highlight differences in public charging coverage and service quality across communities [11,12].

Recent national analyses also show that public charging access and reliability vary across communities, and that disadvantaged communities may experience lower charger availability or lower service quality [11,12]. For public facilities, these findings suggest that planning should include not only charger count but also service probability, queuing, waiting, and the number of vehicles that leave without charging.

2.5 Forecasting EV Arrival and Charging Patterns

For this study, forecasting EV arrival density and charging patterns across seasons, holidays, and weather conditions is central because EVSE demand is stochastic and time-dependent. Public charging infrastructure

has been studied as a planning problem involving station location and deployment decisions [17]. Stochastic EV/PHEV load models further show that charging demand can be represented using probabilistic arrival behavior, charge-duration distributions, queueing theory, and load-forecast uncertainty [18]. Discrete-event and simulation-based EVCS studies further support modeling individual charging behavior, charger availability, and capacity-planning decisions rather than relying only on aggregate energy estimates [23].

EVCS planning reviews also emphasize uncertainty-aware infrastructure planning, charger sizing, grid-upgrade interactions, renewable energy integration, machine learning methods, and multi-objective optimization [9,13,14]. The common conclusion is that EVSE planning should not rely on deterministic average demand alone. Arrival uncertainty, charging duration, charger compatibility, waiting behavior, and the interaction between charging demand and existing facility load must be represented explicitly.

Recent research has increasingly emphasized integrated and data-driven approaches to EV charging-infrastructure planning. Ayoade and Longe [24] reviewed smart electromobility charging infrastructure, emphasizing smart-grid integration, intelligent charging approaches, renewable-energy integration, optimization methods, and emerging charging technologies. Suresh et al. [25] reviewed EV charging-infrastructure planning in power-distribution networks, with particular attention to charging-demand modeling, grid impacts, reliability, and the interaction between charging demand and distribution-system operation. These studies demonstrate that charging-infrastructure decisions increasingly require consideration of demand uncertainty, operational performance, grid capacity, and economic factors within an integrated planning framework.

Other studies have integrated infrastructure deployment with charging and transportation operations. He et al. [26] proposed a two-phase framework that jointly considers charging-infrastructure deployment, battery capacity, and charging schedules for battery-electric bus systems. Sayarshad [27] developed an optimization model that integrates EV routing and charging decisions while accounting for vehicle range and charging requirements. Bai et al. [28] proposed an EV charging-station planning framework that combines dynamic charging-demand prediction with multi-objective siting and sizing optimization while considering EV travel behavior and power-grid load. In addition, Mehouachi et al. [29] applied a robust hybrid approach to EV charging-station planning in an urban case study. Collectively, these studies illustrate the value of linking demand estimation, infrastructure deployment, transportation operations, charging requirements, and grid considerations in EV charging planning.

Jo et al. [30] developed a multi-period framework for large-scale EV charging-station deployment under latent charging demand using a Bayesian optimization-based large neighborhood search approach. Their study demonstrates the importance of accounting for uncertain and evolving charging demand when making long-term infrastructure-deployment decisions. Although their work focuses on strategic, large-scale infrastructure planning, it provides a complementary perspective to the facility-level simulation approach adopted in the present study.

Whereas these studies primarily address strategic infrastructure deployment, location optimization, routing, or charging scheduling, the present study focuses on facility-level feasibility assessment. The proposed framework integrates stochastic EV arrival generation, discrete-event charging simulation, and utility-rate-based cost estimation to evaluate how variations in demand conditions and charger configurations affect charging-service performance, energy consumption, peak demand, and operating cost. Thus, the framework complements broader optimization-based planning approaches by providing an operational and economic assessment of proposed charging infrastructure at the facility level.

2.6 Research Gap and Contribution of the Present Study

The reviewed literature shows three important gaps. First, many national and regional studies estimate infrastructure needs at broad spatial scales, while facility managers need site-specific tools for evaluating charger count, user service, energy use, and cost [4,5,11,14]. Second, many planning studies emphasize siting and coverage, but public facilities also need to understand utility-bill impacts, especially demand charges caused by coincident charging and building load [9,14]. Third, reliability and equity studies show that charger availability and service outcomes matter, meaning the model should account for waiting and vehicles leaving without charging, not only total energy consumption [7,8,12].

This study addresses these gaps by integrating a Monte Carlo EV-arrival generator, a discrete-event charging simulation, and an energy-demand-cost model for a public facility. The framework uses weather- and calendar-sensitive arrival generation, vehicle-type splitting, charger-specific service logic, waiting and departure outcomes, and demand-charge estimation to evaluate whether proposed EVSE configurations are operationally sustainable and economically viable at the facility level. This facility-level emphasis complements official charging-infrastructure need assessments [3–5], charger reliability and resilience evidence [7,8], national coverage and equity analyses [11,12], and recent reviews on optimization and uncertainty-aware EVCS planning [13,14]. The contribution is also aligned with recent grid-aware planning work that combines charging-demand estimation, stochastic charger-location and capacity decisions, and power-system constraints under uncertainty [31].

3 Materials and Methods

3.1 Overview of the Modeling Framework

The modeling framework has five sequential modules: input definition, Monte Carlo arrival generation, discrete-event charging simulation, output processing, and energy-demand-cost estimation. Fig. 1 summarizes the full workflow. The model uses facility-specific inputs and produces outputs that can be directly interpreted by facility managers, including monthly energy use, monthly peak demand, and monthly operating cost.

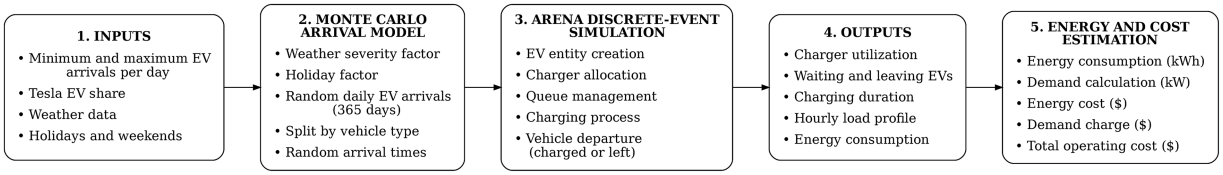


Figure 1: Overall simulation framework for facility-level EVSE feasibility assessment.

3.2 Input Parameters and Assumptions

The core inputs are the minimum daily EV arrivals, maximum daily EV arrivals, percentage of Tesla or Tesla-compatible arrivals, weather severity probability, holiday/weekend calendar, charger count, charger type, charger power rating, charging-duration distribution, and electricity tariff. These variables are consistent with prior EV arrival and charging-demand studies that represent user arrivals, charger availability, charging duration, and stochastic demand as central planning inputs [17,18]. The simulation assumes that daily visitor-related EV arrivals are influenced by weather and calendar effects.

The representative case uses Level 2 charging equipment. The non-Tesla-compatible charger power rating is modeled as 7.2 kW, while the Tesla-compatible charger is modeled as 17.2 kW. The vehicle–charger compatibility assumptions adopted in this study reflect the regional market and charging-infrastructure

conditions considered during model development rather than the full range of compatibility options available across broader EV markets. Within the scope of the representative facility configuration, Tesla-compatible and non-Tesla vehicles were modeled as separate charger categories. This assumption provides a consistent basis for evaluating the selected charging-station configurations under the conditions considered in this study. Future extensions of the framework may incorporate broader market conditions, including adapter availability, shared charger access, and evolving vehicle–charger interoperability standards. In this study, the term "Tesla-compatible charger" refers to the dedicated Tesla-compatible charging resource represented in the simulation. For modeling purposes, Tesla-compatible and non-Tesla vehicles were routed to separate charger categories, and cross-compatibility through charging adapters was not explicitly modeled. Charging duration is modeled with triangular distributions because the minimum and maximum charging times are known more confidently than the full empirical distribution. Non-Tesla charging durations vary from 2 to 6 h and Tesla-compatible charging durations vary from 3 to 6 h. A one-vehicle waiting queue is allowed for each charger category to reflect limited space and long service times.

The triangular probability density function used to generate the charging duration T is expressed as follows:

$$f_T(t) = \begin{cases} \dfrac{2(t-a)}{(b-a)(m-a)}, & a \le t \le m, \\ \dfrac{2(b-t)}{(b-a)(b-m)}, & m < t \le b, \\ 0, & \text{otherwise.} \end{cases}$$

In this expression, a is the minimum charging duration, m is the most probable charging duration, and b is the maximum charging duration. Because detailed empirical charging-session distributions were unavailable, the midpoint m = (a + b)/2 was used as the most probable value. Accordingly, non-Tesla-compatible charging duration was modeled as Triangular (2, 4, 6) h, while Tesla-compatible charging duration was modeled as Triangular (3, 4.5, 6) h. These parameters represent the Level 2 charging equipment considered in the facility case and should not be interpreted as representative of mixed charging networks that include direct-current (DC) fast chargers.

3.3 Monte Carlo EV Arrival Generation

The Monte Carlo module generates an annual sequence of daily arrivals and converts it to hourly arrival schedules. For each day, the algorithm assigns a weather factor (WF) and a holiday factor (HF). If the day is classified as severe weather (WF = 0), the number of arrivals is set to the minimum daily value. If the day is comfortable and non-holiday (WF = 1 and HF = 0), arrivals are set to the average of minimum and maximum daily arrivals. If the day is comfortable and holiday or busy-season day (WF = 1 and HF = 1), arrivals are set to the maximum daily value.

The rule-based daily EV-arrival model can be expressed mathematically as follows:

$$A_d = \begin{cases} A_{\min}, & \mathrm{WF}_d = 0, \\ \dfrac{A_{\min} + A_{\max}}{2}, & \mathrm{WF}_d = 1 \text{ and } \mathrm{HF}_d = 0, \\ A_{\max}, & \mathrm{WF}_d = 1 \text{ and } \mathrm{HF}_d = 1. \end{cases}$$

where A_d is the total number of EV arrivals on day d, $A_{\min}$ and $A_{\max}$ are the assumed minimum and maximum daily arrivals, respectively, and WF_d and HF_d are the binary weather and holiday/calendar factors for day d.

These equations are a mathematical representation of the heuristic decision rules described below; they do not assume a Poisson or other fitted probability distribution for the daily arrival count.

The rule-based structure was selected because the available research-platform data supported broad weather- and calendar-related demand scenarios but were insufficient for calibrating a time-varying probabilistic arrival model. Data-driven approaches such as non-homogeneous Poisson processes can estimate time-varying EV-arrival intensity and better represent arrival peaks when detailed charging-session data are available [32]. Accordingly, the present formulation is intended as a transparent and computationally tractable scenario-generation method rather than a statistically calibrated arrival forecast. Future work may replace or extend these rules using empirically calibrated Poisson or non-homogeneous Poisson arrival processes.

The uniform probability distribution was used in developing the Monte Carlo simulation approach. The model uses repeated randomized draws to generate different daily conditions and annual EV-arrival scenarios. For each day, the weather factor is assigned using a uniform random draw and the specified weather-severity probability. The resulting weather factor, together with the holiday factor, determines whether the number of arrivals is set to the minimum, average, or maximum value. Monte Carlo simulation captures variability in EV charging demand by introducing randomness in weather conditions, vehicle-type allocation, and within-day arrival times. Instead of assuming a single fixed annual schedule, repeated simulation runs can generate diverse stochastic charging scenarios, including variations in peak and low-demand periods.

Table 1 defines the two WF levels. The HF is set to 1 for U.S. federal holidays, weekends, spring break, Thanksgiving week, and summer months. The days immediately before and after spring break, the Thanksgiving break, and the U.S. federal holidays listed in Table 2 were also assumed to have higher EV arrivals because these periods are associated with increased visitor activity at public facilities. Table 3 presents the full WF × HF arrival-outcome matrix.

Table 1: Weather severity levels and corresponding weather factors (WF).

Severity Level	Weather Factor (WF)
Comfortable weather	1
Severe weather	0

Table 2: U.S. federal holidays assigned a holiday factor of HF = 1 in the arrival model.

Holiday	Date
New Year's Day	January 1
Martin Luther King Jr. Day	Third Monday in January
Presidents' Day	Third Monday in February
Memorial Day	Last Monday in May
Independence Day	July 4
Labor Day	First Monday in September
Columbus Day	Second Monday in October
Veterans Day	November 11
Thanksgiving Day	Fourth Thursday in November
Christmas Day	December 25

Table 3: EV arrival outcome levels as a function of weather factor (WF) and holiday factor (HF).

Weather Severity	WF	Time of Year	HF	Number of Arrivals
Severe	0	Working day	0	Minimum
Severe	0	Holiday	1	Minimum
Comfortable	1	Working day	0	Average of min and max
Comfortable	1	Holiday	1	Maximum

After daily arrivals are generated, the total is divided into Tesla-compatible and non-Tesla-compatible arrivals using the assumed Tesla EV fraction. Within-day arrival times are randomized over a 24 h day and aggregated into hourly bins for the discrete-event simulation. Fig. 2 shows the arrival generation procedure.

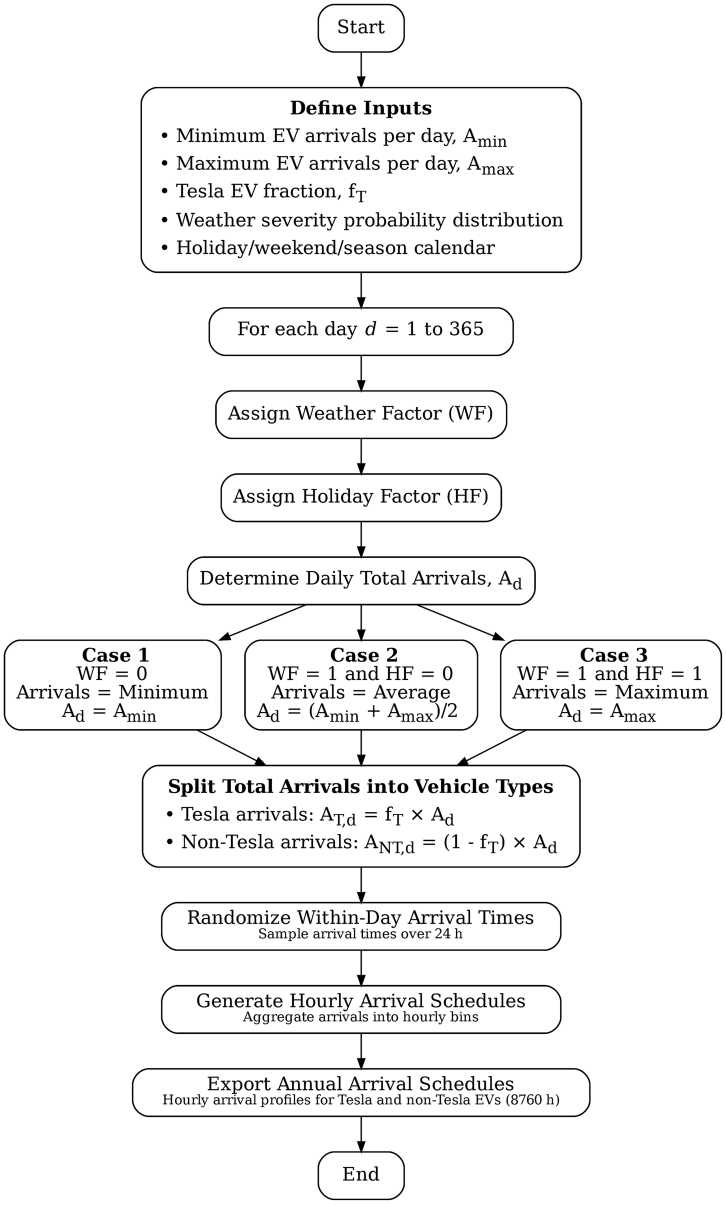


Figure 2: Monte Carlo procedure used to generate daily and hourly EV arrival schedules for the simulation model.

The binary weather and calendar factors provide a simplified representation of EV arrival behavior. The present framework was developed as a preliminary feasibility-assessment tool to examine how variations in EV arrivals affect charger utilization, energy consumption, and peak demand when site-specific charging-demand data are unavailable. The simplified factor structure provides a transparent and reproducible approach for scenario-based analysis; however, it does not capture the full behavioral and temporal complexity of EV charging demand. As additional empirical data become available, the arrival-generation model can be extended to incorporate factors such as travel behavior, trip purpose, land-use characteristics, charging price, battery state of charge, and regional EV adoption patterns.

3.4 Discrete-Event Charging Simulation

The hourly arrival schedules are imported into a discrete-event simulation. Each EV is created as an entity with attributes including arrival time, vehicle type, charger compatibility, charging duration, and energy requirement. Vehicles are routed by type: Tesla-compatible vehicles are routed to Tesla-compatible chargers, while non-Tesla vehicles are routed to non-Tesla chargers.

When a compatible charger is available, the vehicle seizes the charger, undergoes a charging delay, releases the charger, and exits the system as served. If no compatible charger is available, the vehicle enters a one-vehicle queue. If the charger does not become available while the queue position is occupied, the vehicle leaves without charging. The simulation records arrival time, waiting time, charging time, total time in system, charger utilization, served vehicles, and vehicles leaving without charge. A discrete-event simulation does not represent just one single queueing model; instead, it uses a highly flexible, event-driven framework to replicate complex queueing networks. It can represent basic setups such as single-server or multi-server systems by tracking specific entities, service capacities, routing rules, and waiting policies. However, the distributions and externally generated arrival schedules used in the present simulation do not imply a single conventional queueing model such as M/M/C or M/G/C. The assumption that only one vehicle is allowed in the waiting queue for each charger category was based on the regional infrastructural and vehicle-staging considerations used in developing the research and the resulting simulation scenarios. Fig. 3 illustrates the discrete-event modeling procedure.

3.5 Energy Demand and Cost Estimation

Charging-event outputs are converted into hourly energy and demand estimates. For each charging event, energy is calculated as the product of charger power and charging duration. Hourly energy is aggregated by summing all charging events occurring within the same hour. Monthly peak demand is defined as the maximum hourly demand observed in each billing month.

Operating cost is estimated using an electricity tariff with both energy and demand components. Monthly energy cost is computed from total monthly energy consumption and the energy rate. Monthly demand charge is computed from monthly peak demand and the demand-charge rate. Total monthly operating cost is the sum of energy and demand charges. This demand-aware treatment is consistent with EVCS planning literature that treats charger deployment, grid capacity, and demand uncertainty as connected planning concerns [18,20,21]. The demand-charge calculation uses hourly demand values to maintain consistency with the temporal resolution of the Monte Carlo simulation framework and to facilitate the computational analysis. Although many commercial utility tariffs determine billing demand using shorter intervals, such as 15-min demand windows, the hourly resolution provides a practical basis for the planning-level assessment conducted in this study. However, hourly averaging may smooth short-duration charging peaks and may therefore affect the estimated maximum demand and associated demand charges. Accordingly, the reported demand-cost results should be interpreted within the hourly-resolution

framework. Future work may extend the model to 15-min demand intervals to provide a more detailed representation of utility demand-charge calculations. Fig. 4 summarizes the calculation procedure.

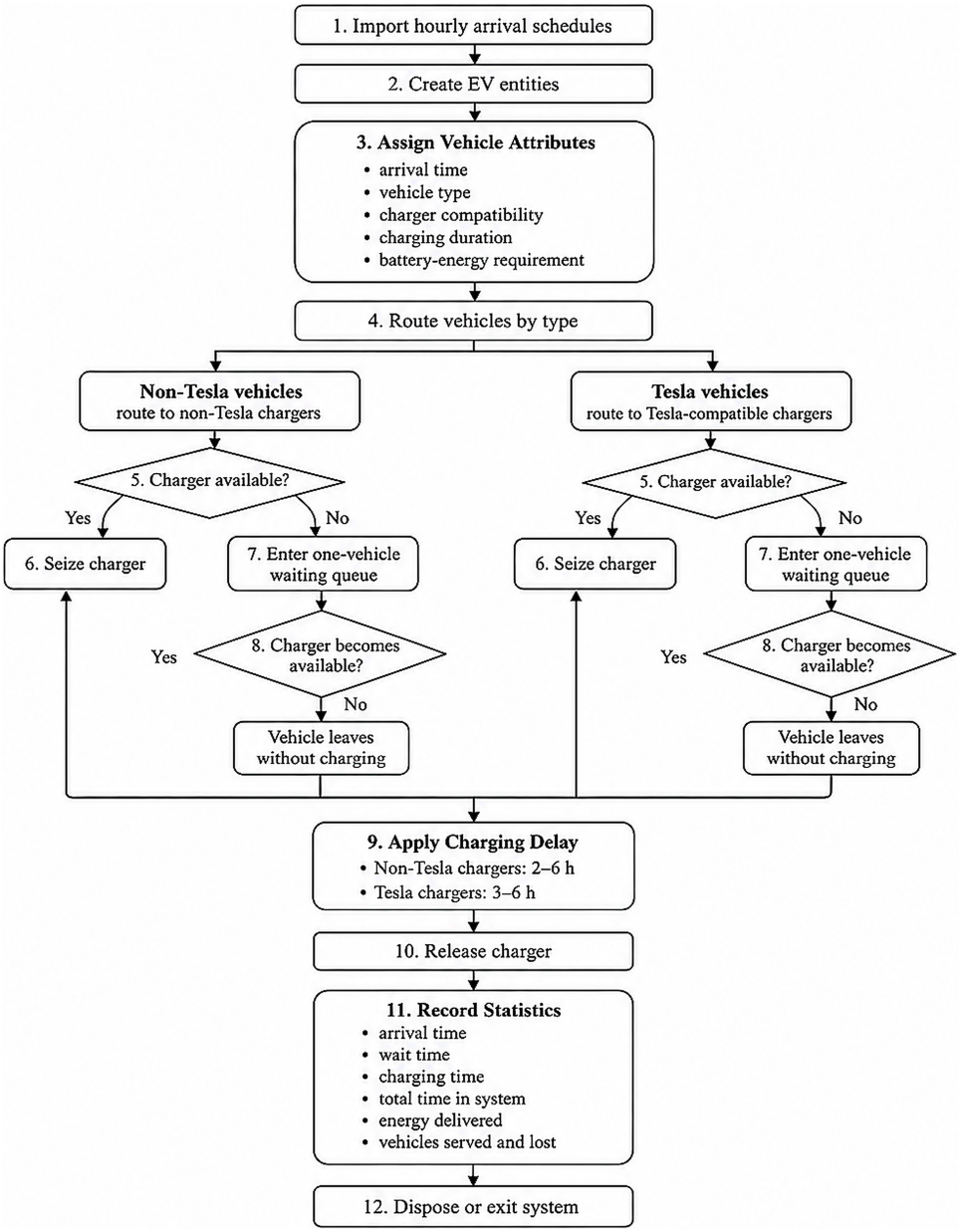


Figure 3: Discrete-event simulation logic for charger allocation, waiting, charging, and departure.

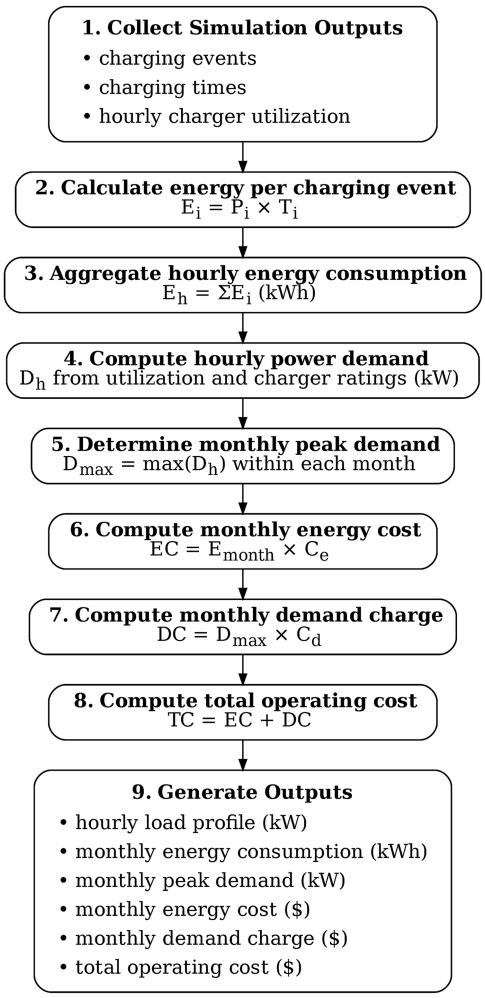


Figure 4: Procedure used to estimate hourly demand, monthly energy consumption, peak demand, and total operating cost from the simulation outputs.

4 Results and Analysis

This section presents the representative facility case and the sensitivity analyses used to evaluate EVSE feasibility. Monthly trends are shown using figures, and compact summary tables are used to report the main scenario-level results. Additional workflow details are included to clarify how the spreadsheet arrival model, Arena discrete-event model, and demand-cost calculations were linked.

4.1 Facility Energy Assessment and Scenario Setup

The representative public facility was evaluated as a commercial electricity customer because utility providers bill such facilities using rate schedules that include both energy charges and demand charges. In the facility energy assessment, the facility consumed 7,516,720 kWh in 2015. Utility-bill review was performed to understand the major monthly energy consumers, estimate average energy and demand costs, and determine whether EVSE installation could be evaluated under a more favorable rate schedule. The rate structure used for the post-simulation cost estimates included an energy charge of $0.0526/kWh and a demand charge of $11.508/kW-month. The baseline EV-arrival case produced 2115 annual EV arrivals, including 850 Tesla-compatible arrivals and 1265 non-Tesla arrivals. This corresponds to a Tesla-compatible share of 40.2%, which

is consistent with the 0.4 Tesla-arrival fraction used in the representative model run. The baseline simulation summarized in Table 4 used a weather-severity probability of 0.3, with minimum and maximum daily arrivals of 0 and 10, respectively. Table 4 summarizes the baseline scenario before the demand and cost calculations are interpreted.

Table 4: Baseline arrival-generation summary.

Metric	Value	Interpretation
Annual EV arrivals	2115	Total simulated Plug-in Electric Vehicle (PEV) arrivals over one year.
Vehicle mix	850 Tesla-compatible; 1265 non-Tesla	Tesla-compatible share = 40.2%, matching the 0.4 input fraction.
Highest-arrival month	June (250 EVs)	Late spring/early summer conditions produced the highest activity.
Calendar/weather indicators	268 WF = 1 days; 204 HF = 1 days	Used for comfortable-weather and high-visitor-period logic.
Weather-severity probability	0.3	Baseline probability used in the representative EV-arrival simulation

4.2 EV Arrival Spreadsheet and Arena Simulation Execution

The EV arrival pattern was generated using a spreadsheet workflow. Before a new run, the model clears previous simulated data and then accepts user inputs for minimum daily EV arrivals, maximum daily EV arrivals, Tesla-compatible EV fraction, and weather-severity probability. For the representative arrival-pattern demonstration, the sample inputs were minimum arrivals = 0, maximum arrivals = 10, Tesla-compatible probability = 0.4, and weather-severity probability = 0.3. After these inputs were entered, the model generated daily EV arrivals for a 365-day year, separated the total arrivals into Tesla-compatible and non-Tesla EVs, and produced random arrival times for each vehicle type over the simulated year.

The spreadsheet then converts the arrival times into hourly schedules for the Arena discrete-event model. Separate schedules are produced for Tesla-compatible and non-Tesla vehicles so that the charging simulation can route each entity to the appropriate charger type. For the representative charging-pattern simulation, the model used two Schneider-type Level 2 chargers and one Tesla-compatible charger, which enables the charging-station configuration sensitivity analysis reported later in this section.

4.3 Weather-Severity Sensitivity

The weather-severity sensitivity analysis compared two probability settings while holding the other key arrival inputs constant. Specifically, the weather-severity probabilities were set to 0.5 and 0.4, while the minimum daily arrivals, maximum daily arrivals, and Tesla-compatible probability were held at 0, 5, and 0.3, respectively. Figs. 5–7 show the monthly peak-demand, energy-consumption, and operating-cost patterns. The purpose of these figures is to show the timing of peaks and dips across the year; Table 5 gives a compact numerical summary without duplicating every monthly value in the manuscript body.

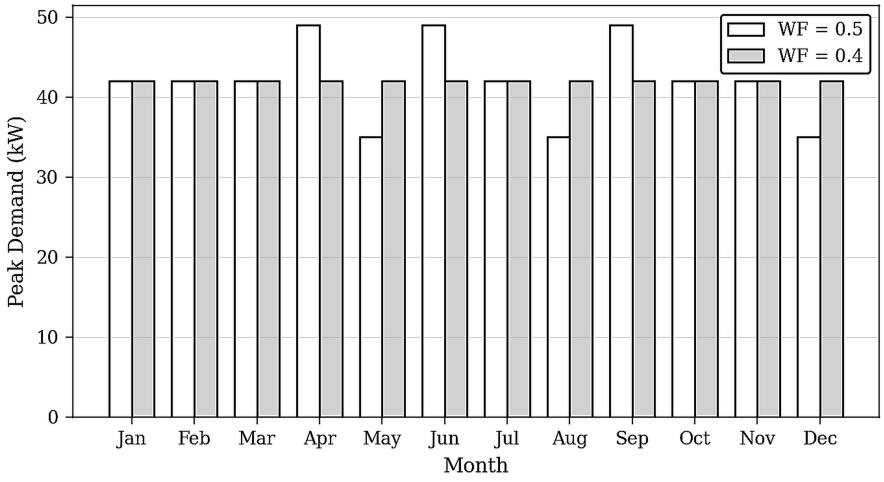


Figure 5: Monthly peak demand under weather severity probabilities of 0.5 and 0.4.

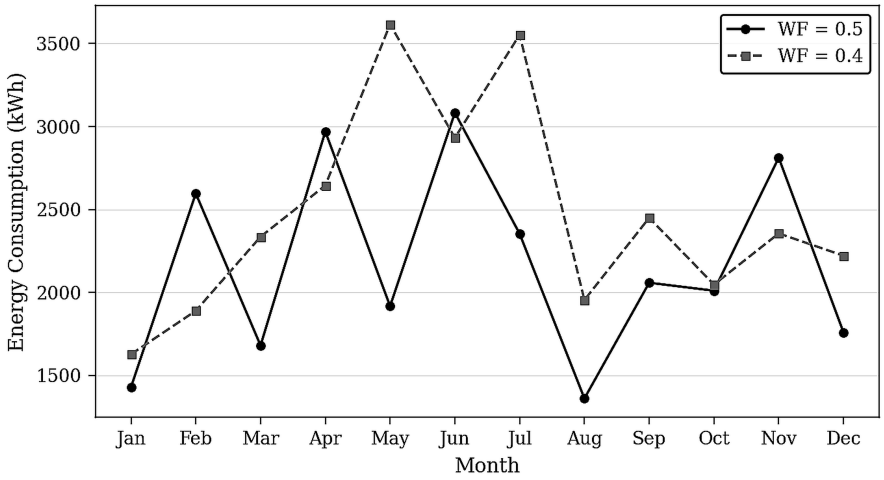


Figure 6: Monthly EV charging energy consumption under weather severity probabilities 0.5 and 0.4.

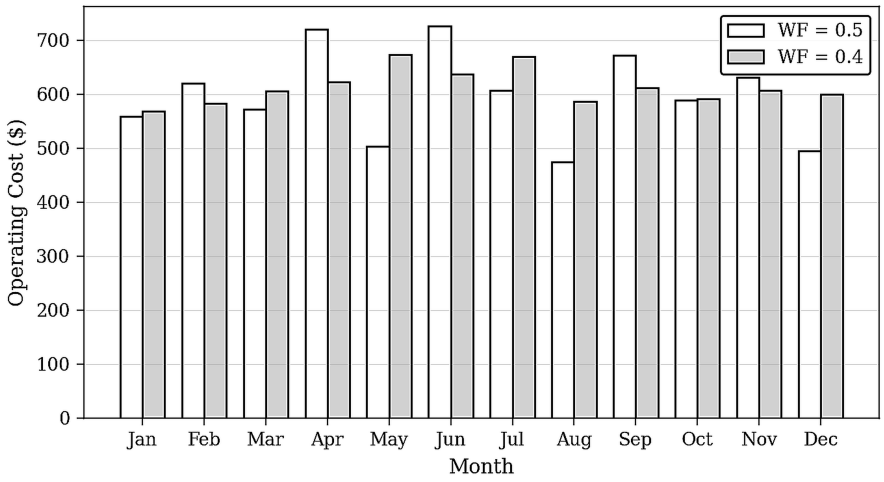


Figure 7: Monthly total operating cost under weather severity probabilities 0.5 and 0.4.

Table 5: Summary of weather-severity scenario outputs.

Scenario	Peak-Demand Range (kW)	Annual Energy (kWh)	Annual Operating Cost ($)	Highest-Cost Month
WF = 0.5	35–49	26,037	7,169.59	June
WF = 0.4	42 (constant across all months)	29,631	7,358.62	May

The WF = 0.4 case produced higher annual EV charging energy than the WF = 0.5 case, but its peak demand remained constant at 42 kW in the representative run. This confirms that monthly demand cost cannot be inferred from annual or monthly energy alone. Energy increases with the total number and duration of charging events, whereas peak demand depends on the coincidence of charging events within the billing interval and with the existing facility load.

4.4 Charging-Station Configuration Sensitivity

The charger-configuration analysis compared three scenarios while holding the minimum daily arrivals, maximum daily arrivals, Tesla-compatible probability, and weather-severity probability constant. The weather-severity probability was set to 0.3, with minimum arrivals = 0, maximum arrivals = 5, and Tesla-compatible probability = 0.3. The three configurations were defined as follows: one Schneider-type and one Tesla-type charger (1S–1T), one Schneider-type and two Tesla-type chargers (1S–2T), and three Schneider-type and two Tesla-type chargers (3S–2T). Figs. 8–10 show the monthly patterns for peak demand, energy consumption, and total operating cost. The charging-station configurations are denoted as 1S–1T, 1S–2T, and 3S–2T, where S represents a Schneider-type Level 2 charger and T represents a Tesla-compatible charger. Table 6 summarizes the annual peak demand, energy consumption, and operating cost for the three charging-station configurations.

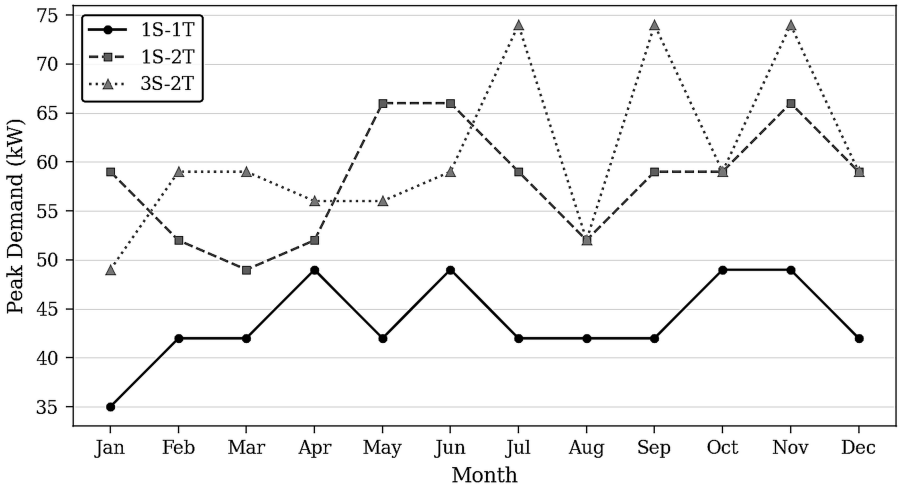


Figure 8: Monthly peak demand for the 1S–1T, 1S–2T, and 3S–2T charging-station configurations.

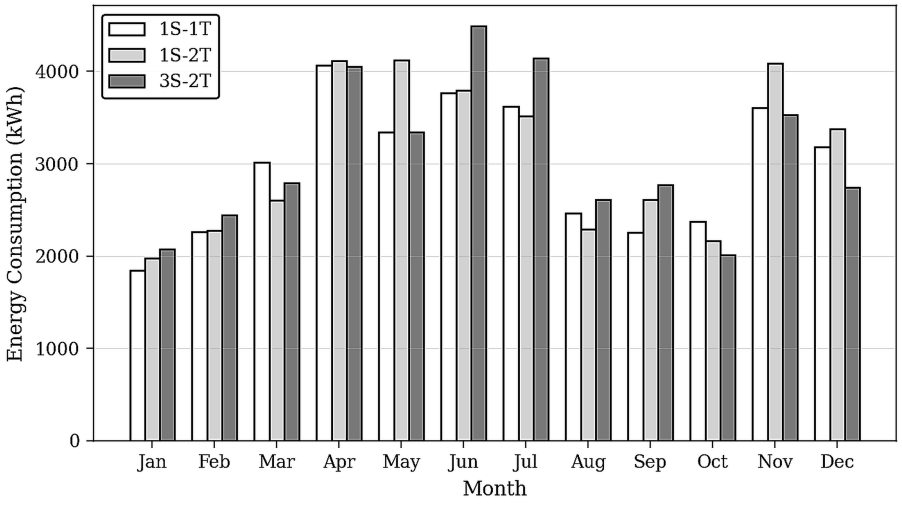


Figure 9: Monthly EV charging energy consumption for the 1S–1T, 1S–2T, and 3S–2T charging-station configurations.

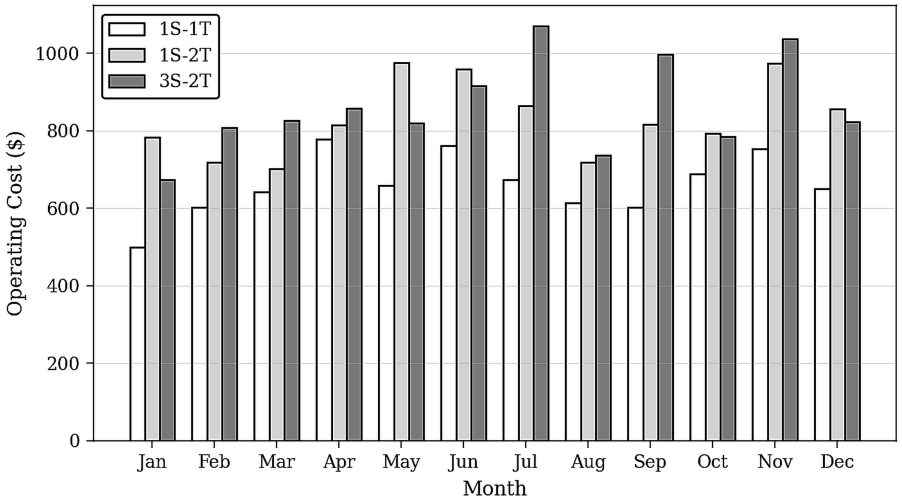


Figure 10: Monthly total operating cost for the 1S–1T, 1S–2T, and 3S–2T charging-station configurations.

Table 6: Summary of charging-station configuration outputs.

Configuration	Maximum Monthly Peak (kW)	Annual Energy (kWh)	Annual Operating Cost ($)
1S–1T	49	35,783	7,923.88
1S–2T	66	36,915	9,974.30
3S–2T	74	36,993	10,346.67

The configuration results show the central trade-off in public-facility EVSE planning. Increasing charger count allows more charging to occur and can reduce the number of vehicles leaving without charge, but it can also increase the monthly peak demand and the demand-charge component of the utility bill. Therefore, the economically preferred configuration is not necessarily the configuration with the highest

number of chargers; it depends on service objectives, facility load coincidence, and tolerance for additional demand charges.

4.5 Model Verification, Scenario Evidence, and Limitations

The model workflow provides internal verification evidence through input-to-output traceability rather than through formal statistical validation. The arrival spreadsheet clears previous data, accepts user inputs, generates daily EV arrivals, separates arrivals by vehicle type, creates random arrival times, and converts those times into Arena-compatible hourly schedules. The Arena-based charging simulation then reads the schedules, creates EVs as entities, assigns vehicle attributes, routes vehicles by charger compatibility, applies queueing and charging logic, and writes simulation results to spreadsheet output files.

The first output file reports event-level results, including arrival times, waiting times, charging times, and energy and cost estimates for individual charged vehicles. The second output file reports hourly resource utilization, charging-station load, building load, total hourly demand, hourly energy consumption, monthly energy consumption, monthly peak demand, and associated energy and demand costs. The demand worksheet is especially important because monthly peak demand is taken as the maximum one-hour rolling total demand in each month. Demand cost attributable to the charging stations can be estimated by multiplying the charging-station load contribution at the monthly peak hour by the demand-charge rate.

Five hundred Monte Carlo simulation runs were performed for each scenario using the simulation platform. These runs were used to evaluate the decision-support framework for assessing sustainable electric vehicle charging-station configurations by representing uncertainty in weather severity, time of year, vehicle-arrival patterns, vehicle-type allocation, and within-day arrival timing. The reported scenario values were obtained by averaging the measured outputs across the 500 independent simulation runs. A detailed examination of confidence intervals and uncertainty bounds is being developed as part of separate research and is therefore outside the scope of the present study.

The main limitations are as follows. First, EV arrivals are simulated using weather severity and time-of-year logic based on minimum and maximum arrival assumptions rather than measured long-term EVSE field arrivals. Second, the model uses one-hour time slots, so the demand analysis is based on one-hour rolling peaks rather than 15-min utility demand intervals. Third, although 500 independent Monte Carlo simulation runs were performed for each scenario and the measured outputs were averaged to obtain the reported scenario values, detailed replication-level statistics were not retained in the final reporting dataset. Therefore, standard deviations, confidence intervals, and formal uncertainty bounds cannot be reconstructed from the summarized average values. The reported results should consequently be interpreted as scenario-based planning estimates rather than statistically generalized forecasts.

5 Discussion

The results demonstrate that EVSE feasibility for public facilities is sensitive to time-dependent demand behavior, charger availability, and electricity tariff structure. The figures and summary tables show that energy consumption, peak demand, and total operating cost do not move identically. This is important because demand charges are triggered by monthly peak coincidence, whereas energy charges accumulate with total charging duration. A charger configuration that serves more vehicles can therefore improve user service while also increasing peak-demand exposure and total monthly cost.

The modeling framework has practical value because it allows facility managers to use readily available inputs, including historical visitor ranges, expected EV share, weather or seasonal patterns, charger power ratings, and utility rates. It also produces interpretable outputs such as served vehicles, vehicles leaving

without charging, energy use, peak demand, and operating cost. These outputs can support capital planning, utility-rate review, and demand-management strategies, while also addressing the service-reliability concerns emphasized in recent public charging research [7,8,12].

Although the arrival-generation model was not calibrated using site-specific charging-session data, its general structure reflects characteristics of EV charging demand discussed in the literature, including temporal variation in vehicle arrivals, variation in charging duration, and differences in charging demand associated with charger type and charging rate. However, the present study does not constitute a formal empirical validation of these characteristics. A comprehensive comparison using observed arrival times, charging-session records, vehicle dwell times, and facility electricity-demand data is reserved for future work.

Because the arrival-generation model uses simplified weather and calendar factors rather than observed charging-session data, the resulting demand profiles should be interpreted as scenario-based feasibility estimates rather than statistically validated forecasts. Future studies should calibrate and validate the model using site-specific EVSE utilization data and incorporate additional factors related to travel behavior, trip purpose, land-use characteristics, charging price, battery state of charge, and regional EV adoption patterns.

The present study represents a preliminary implementation of the simulation framework. Stochastic variation is introduced through the Monte Carlo arrival-generation procedure using uniform probability distributions; however, formal statistical analysis of the replication-level outputs, including standard deviations, confidence intervals, and significance analyses, was not conducted within the scope of the present study. Therefore, the reported results should be interpreted as preliminary scenario-based outcomes rather than statistically generalized estimates. Future EVSE planning should also account for charger reliability, equity of access, geographic coverage, grid-capacity interactions, and uncertainty-aware sizing [11–14]. The proposed framework can be expanded to include reliability parameters, downtime events, maintenance cost, real-time electricity pricing, charging revenue, renewable energy generation, battery storage, and 15-min demand intervals. Future work should retain and analyze the replication-level outputs from multiple independent stochastic replications for each scenario and report confidence intervals for key outputs, including monthly peak demand, service probability, energy consumption, and operating cost.

6 Conclusions

This research developed and demonstrated a simulation-based framework for forecasting PEV arrival traffic density and charging behavior at a public facility over a full year. The approach combines a Monte Carlo arrival-generation model with a discrete-event charging simulation. The Monte Carlo module uses pre-recorded and categorical inputs, including minimum and maximum daily arrivals, weather severity, holidays, weekends, vacation periods, and time-of-year effects, to generate annual arrival patterns. These generated arrivals are then used as inputs to the discrete-event simulation, which models charger compatibility, queueing, charging duration, charger release, served vehicles, and vehicles leaving without charging.

The study also performed a demand analysis for the considered public facility by estimating the electrical supply requirements associated with EV charging at different times of the year. The resulting hourly demand, energy consumption, monthly peak demand, and operating-cost estimates provide a basis for evaluating demand-curtailment strategies and potential savings in demand charges. The simulated data can also be used to examine whether a change in utility rate schedule would reduce the demand-charge burden after adding charging stations.

For the representative facility analyzed in this study, the possibility of reducing demand charges through a rate-schedule change was limited. The facility was already billed under the utility provider's rate schedule for large demand-drawing facilities, and the kilowatt demand values obtained from multiple simulation runs

exceeded the facility's existing larger peak-demand condition. Therefore, the facility would remain under the same demand-based rate schedule, indicating that demand-charge reduction could not be achieved simply by changing the existing billing schedule.

The results further show that the monthly electrical peak demand is not governed only by the number of installed charging stations or the number of vehicles charging simultaneously. It also depends on the coincident demand from the rest of the facility buildings. In some months and hours, the charging stations and building loads jointly establish the facility peak; in other periods, the buildings alone establish the peak even when EV charging is present. This distinction is important because it shows why EVSE feasibility must be evaluated using combined facility-load and charging-load profiles rather than charging energy alone.

The developed tool is capable of estimating the total facility demand as well as separating the demand drawn by the charging stations and the remaining building loads for every hour of the simulated year. This hourly separation helps users understand demand behavior, identify the timing of peak-demand formation, and take strategic actions to reduce monthly peak demand. Such actions may include charger scheduling, demand response, limiting simultaneous charging, revising operating policies, or coordinating EVSE use with building load-management strategies.

Overall, the simulated energy consumption, demand, and cost outputs can support decisions on the optimal number and type of charging stations to install in a public facility. By comparing weather-severity conditions, charger configurations, energy use, demand charges, and total operating cost, the framework helps identify EVSE deployment options that are operationally sustainable, economically viable, and better aligned with facility-level electrical constraints.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

Abbreviation	Full Term
BEV	Battery electric vehicle
EV	Electric vehicle
EVSE	Electric Vehicle Supply Equipment
EVCS	Electric Vehicle Charging Station
GHG	Greenhouse gas
HF	Holiday factor

PEV	Plug-in electric vehicle
PHEV	Plug-in hybrid electric vehicle
WF	Weather factor

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