Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260399
Published: June 9, 2026

An Integrated Data-Driven Framework for EV Charging Demand and Service Level

Muhammad Nadeem Akram and Walid Abdul-Kader
Industrial Engineering Program, MAME Department
University of Windsor, Windsor, Ontario, Canada
Akram113@uwindsor.ca, kader@uwindsor.ca

Abstract

The increasing adoption of electric vehicles poses significant challenges for charging infrastructure planning and grid integration under dynamic traffic conditions. This study presents a traffic informed EV charging demand estimation framework for EV charging infrastructure planning by integrating observed traffic flow data, EV charging demand estimation, energy demand modeling, and G/G/C queueing analysis. A case study is conducted on the Huron Church Road-Highway 401 corridor in Windsor, Ontario, Canada, using lane level hourly traffic data collected across seven lanes. EV charging demand is estimated using an EV penetration rate of 3.4% and a charging station capture rate of 4%, while charging load is calculated based on an average energy consumption of 50 kWh per EV. The results estimate a current charging demand of approximately 48 EVs/day, with a peak arrival rate of 3.25 EVs/hr, corresponding to a peak traffic flow of 2,389 vehicles/hr and a peak charging load of 162.5 kWh/hr (0.163 MW). Scenario analysis shows that under higher EV penetration levels, charging demand may increase to approximately 706 EV/day, with peak load reaching approximately 2.39 MW. Queueing analysis demonstrates that charger configuration significantly affects system performance. Compared with a two-charger configuration, a three-charger system reduces utilization from 0.475 to 0.317 and decreases average waiting time to approximately 5.8 minutes under the Kramer Langenbach Belz (KLB) approximation. The proposed framework provides an integrated transportation energy approach for scalable EV charging infrastructure planning, supporting grid operators, policymakers, and infrastructure planners under future electrification scenarios.

Keywords

Electric Vehicles; Charging Infrastructure; Queuing Theory; Traffic Flow Modeling; Sustainable Transportation

1. Introduction

The rapid expansion of electric vehicles (EVs) has significantly increased global interest in sustainable transportation systems, driven by concerns over greenhouse gas emissions (GHG), air pollution, and dependence on fossil fuels. Countries including Canada are actively promoting EV adoption through policy incentives, infrastructure investments, and long term net-zero emission targets. As EV penetration continues to grow, the development of efficient and reliable charging infrastructure has become a critical requirement for ensuring the stability and usability of electrified transportation networks (Akram and Abdul-Kader, 2026). Despite this progress, EV charging infrastructure planning remains a complex challenge. Charging stations must be designed to manage highly variable demand, reduce waiting times, and avoid both underutilization and congestion (Masrur et al. (2025). Traditional planning approaches often rely on aggregated indicators such as Annual Average Daily Traffic (AADT) or simplified demand assumptions. While useful for macro-level planning, these approaches fail to capture temporal variability, stochastic driver behavior, and peak-hour congestion effects, leading to suboptimal infrastructure sizing.

Recent studies have introduced traffic flow based modeling, stochastic arrival processes, and queuing theory for EV charging analysis. However, many of these approaches still rely on static or simplified arrival assumptions that do not fully reflect real world traffic dynamics. Similarly, commonly used queuing models such as M/M/1 and M/M/C often lack direct integration with observed traffic data. In addition, the interaction between EV charging demand and electrical grid loading remains insufficiently addressed, particularly under peak congestion conditions where high charging demand can significantly stress distribution networks.

To address these limitations, this study proposes a data-driven integrated framework that directly links lane level traffic flow data with EV charging demand estimation. The framework incorporates a time varying stochastic arrival process, converts mobility demand into electrical load profiles, and evaluates system performance using a G/G/C queuing model. A case study is conducted on a major transportation corridor in Windsor, Ontario, Canada, which represents a mixed commuter, freight, and cross border traffic environment. This enables realistic modeling of EV charging behavior under real traffic conditions.

The main contributions of this paper are fourfold. First, it develops a traffic informed EV charging demand estimation framework that links observed traffic flow data with estimated EV charging demand for realistic infrastructure planning using EV penetration and charging station capture rate assumptions. Second, it applies a time varying stochastic arrival model to capture dynamic EV arrival behavior. Third, it integrates transportation demand with electrical load estimation to generate hourly charging profiles for grid planning. Finally, it evaluates system performance using a G/G/C queuing model to identify optimal charger configuration under real world variability. The remainder of this paper is organized as follows: Section 2 reviews the relevant literature, Section 3 presents the methodology, Section 4 discusses results and system performance, and Section 5 concludes the study.

2. Literature Review

The rapid growth of EV has intensified research on charging infrastructure planning, demand forecasting, and grid integration. Existing studies can be broadly categorized into four areas: EV demand modeling, traffic-based approaches, stochastic arrival modeling, and queuing theory applications. Among these, queuing theory remains a widely used tool for evaluating EV charging station performance, with the classical M/M/C model serving as a foundational framework. This model assumes Poisson arrivals, exponentially distributed service times, and parallel chargers; however, such assumptions often limit its applicability under real-world traffic conditions.

Recent studies have expanded beyond these simplifications. Shaat et al. (2026) develop a scenario based framework to assess EV charging demand and economic feasibility in Abu Dhabi through 2050, projecting EV stocks of 750,000 (Progressive) and 1.1 million (Thriving). While the Thriving scenario requires higher investment (108 million AED), it achieves better utilization, improves spatial equity (Gini = 0.27), and stronger long term returns. Nevertheless, only 17.6% of communities meet infrastructure readiness thresholds, highlighting the need for coordinated grid expansion and equitable deployment. Liao et al. (2026) propose a flexible scheduling strategy to redistribute peak load using spatiotemporal charging and mobility data from Shanghai (2018-2024). Their approach integrates EV adoption and population growth projections to optimize charging station deployment and estimate additional emissions from power dispatch. Similarly, Mao et al. (2026) introduce a data-driven integrated learning framework based on high dimensional anonymized charging station data from Jiangsu Province, China. The model combines ensemble learning methods Random Forest (RF), Gradient Boosting Decision Trees (GBDT), and Light GBM with a BiLSTM deep learning model, while hyperparameters are optimized using the Dung Beetle Optimization (DBO) algorithm. Key predictors include operational characteristics of charging stations and time-series features.

To better capture real world variability, several studies have extended traditional queuing formulations. Soufiani et al. (2026) develop a multi server queuing model in which EV arrivals follow a Markovian Arrival Process (MAP) and charging times follow a Phase Type distribution. Their findings identify a minimum charging probability threshold required for system stability. Masrur et al. (2025) propose an M1/M2/C model with time varying arrival rates, demonstrating that congestion persists under fluctuating demand and that peak charging demand closely aligns with daytime traffic patterns. Operational improvements have also been explored. Liu (2025) shows that optimized charger allocation, reservation systems, and priority scheduling can significantly reduce waiting times and enhance service efficiency. The study further highlights that integrating energy storage within queue based control frameworks improves grid stability by mitigating peak load stress. Meng et al. (2024) introduce a time based scheduling strategy using an M/M/s/K model, allocating EVs and electric buses across peak and off-peak periods to enhance system performance. Pourvaziri et al. (2024) develop a hybrid optimization framework integrating queuing theory, deep learning, and optimization techniques to jointly determine station location, capacity, and vehicle assignment, achieving reductions in both waiting time and operational cost.

Overall, the literature consistently demonstrates that limited charging capacity leads to sharp increases in waiting time, while moderate capacity expansion significantly improves system performance. However, most existing studies rely on simplified or assumed arrival processes and often neglect real traffic data, limiting their ability to capture dynamic transportation conditions. To address these gaps, this study proposes an integrated framework that directly links lane level traffic data with EV charging demand estimation. It incorporates time varying stochastic arrival processes, converts traffic flow into electrical load profiles, and evaluates system performance using a G/G/C queuing model. This approach enables more realistic representation of EV charging behavior under traffic driven variability and supports infrastructure design aligned with real-world conditions.

2.1 Research Gap

Despite extensive research on EV charging systems, several critical gaps remain. First, most existing models do not directly integrate real world traffic data with queuing based EV charging analysis, relying instead on assumed or synthetic arrival processes. This limits the realism of demand estimation. Second, many studies use static or aggregated demand assumptions, which fail to capture temporal variability and peak hour congestion effects. Third, the coupling between transportation demand and electrical load modeling remains weak, with limited translation of mobility patterns into time dependent energy demand profiles for grid planning. Finally, there is a lack of corridor level empirical validation using high resolution traffic datasets, reducing the practical applicability of many proposed models. To address these limitations, this study introduces a unified traffic informed EV charging demand estimation framework that integrates observed traffic flow, stochastic EV arrival estimation, and G/G/C queueing analysis using Allen Cunneen (AC), Kramer Langenbach Belz (KLB), and Kimura approximations to enable more accurate and scalable EV charging infrastructure planning.

2.2 Primary Contributions

- To develop a traffic informed EV charging demand estimation framework using lane level traffic data for improved corridor level reconstruction and EV demand estimation, and to apply a time varying stochastic arrival model to capture dynamic EV charging behavior under real traffic conditions.
- To integrate transportation demand with electrical load modeling to generate hourly EV charging load profiles for grid planning.
- To apply a G/G/C queuing framework using AC, KLB, and Kimura approximations to evaluate system performance under general arrival and service distributions.
- To identify optimal charger configuration, demonstrating reduced waiting time, improved utilization, and stable system performance.
- To provide actionable insights for electricity providers and grid operators through hourly load profiling for demand forecasting and infrastructure planning.

3. Methodology

This study develops a data-driven framework that converts lane level traffic flow into EV charging demand and evaluates system performance using stochastic modeling and G/G/C queuing framework using AC, KLB, and Kimura approximations. The framework integrates traffic reconstruction, EV demand estimation, energy transformation, and queueing analysis. Figure 1 shows the proposed framework.

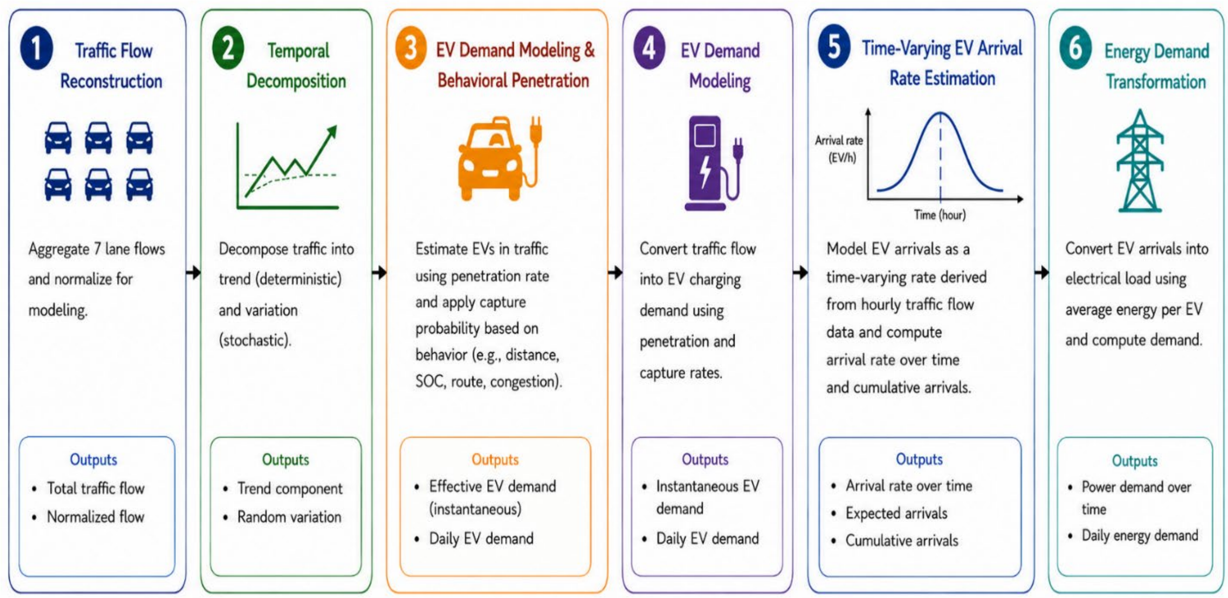

Figure 1. Traffic-Driven EV Charging Demand Modeling

1. Traffic Flow Reconstruction
Traffic from seven lanes is aggregated and normalized for modeling.

$$Flow(t) = \sum_{i=1}^{7} L_i\,(t) \qquad (1)$$

$$Flow_{norm}(t) = \frac{Flow(t)}{\max(Flow)} \qquad (2)$$

Where: $Flow(t)$ denotes total traffic flow; $L_i(t)$ is lane wise flow; $Flow_{norm}(t)$ denotes normalized flow.
Although EV demand is estimated at the corridor level, lane level traffic data are used in the initial reconstruction step to capture spatial heterogeneity across lanes (e.g., directional imbalance and congestion variation).

2. Temporal Decomposition
Traffic is split into trend and random variation.

$$Flow(t) = \bar{F}(t) + \epsilon(t) \qquad (3)$$

Where: $\bar{F}(t)$is deterministic trend; $\epsilon(t)$is stochastic variation.

3. EV Demand Modeling and Behavioral Penetration
Traffic flow is converted into EV charging demand using EV penetration and station capture probability. First, the number of EVs in the traffic stream is estimated from total flow:

$$EV_{base}(t) = Flow(t)\ X\ p_{EV} \qquad (4)$$

Since not all EVs require charging at the corridor, a behavioral capture mechanism is introduced, depending on travel distance, state-of-charge, route choice, and congestion effects:

$$p_{capture} = f(d, SOC, route, congestion) \qquad (5)$$

For modeling purposes, the probability that an EV uses the charging station is approximated as $p_{capture} = 0.04$ (Akram and Abdul-Kader, 2026). The EV charging demand is then derived in two steps: (i) estimation of hourly EV arrivals requiring charging, and (ii) aggregation to daily demand.
The hourly EV charging demand is defined as:

$$EV(t) = Flow(t) \times p_{EV} \times p_{capture} \qquad (6)$$

where $EV(t)$represents the expected number of EVs requiring charging service during hour t.
The corresponding daily EV charging demand is obtained by summing hourly demand over the analysis period:

$$EV_{daily} = \sum_{t=1}^{24} EV(t) \qquad (7)$$

4. **EV Demand Modeling**
Traffic is converted into EV charging demand using penetration and capture rates.

$$EV(t) = Flow(t) \times p_{EV} \times p_{capture} \qquad (8)$$

$$EV_{daily} = Flow_{daily} \times p_{EV} \times p_{capture} \qquad (9)$$

where $EV(t)$represents the expected number of EVs requiring charging during hour t, derived by converting observed traffic flow into EV specific demand using the EV penetration rate and the probability that an EV uses the charging station. EV_{daily}represents the total daily EV charging demand obtained by aggregating hourly traffic over the study period and applying the same penetration and capture assumptions. Here, $p_{EV}$is the proportion of EVs in the traffic stream, while $p_{capture}$denotes the probability that an EV selects and utilizes the considered charging station under corridor travel conditions.

5. Time Varying EV Arrival Rate Estimation
EV arrivals at the charging station are modeled using a time varying arrival rate derived from hourly traffic flow data. Since traffic flow fluctuates during different hours of the day, the EV arrival rate varies over time.
The EV arrival rate is defined as:

$$\lambda_{EV}(t) = EV(t) \qquad (10)$$

where:
$\lambda_{EV}(t)$= EV arrival rate at time t(EV/h)
$EV(t)$ = estimated number of EVs arriving during hour t.

This formulation directly converts observed traffic-based EV demand into a time dependent arrival rate. The resulting $\lambda_{EV}(t)$ is used to generate interarrival times for the G/G/C queuing model, which considers variable EV arrival and charging durations.

6. Energy Demand Transformation
EV arrivals are converted into electrical load demand.

$$Load(t) = \lambda_{EV}(t)\ X\ E_{avg} \qquad (11)$$
$$E_{daily} = \int_0^{24} Load(t)\, dt \qquad (12)$$

Where: E_{avg} is energy per EV; and $Load(t)$ denotes power demand; $E_{avg} = 50$kWh

7. The EV charging station is modeled as a G/G/C queue using Allen-Cunneen (AC), Kramer-Langenbach-Belz (KLB), and Kimura approximations, where both interarrival and service times follow general distributions. This formulation captures real world variability in EV arrivals driven by traffic conditions and in charging times influenced by battery state-of-charge and charger characteristics. The service time is directly linked to the assumed energy requirement per EV and the effective charging power rate, ensuring consistency with the energy demand transformation. Since exact analytical solutions for G/G/C systems are not available, approximation methods are required. As noted by Sztrik (2012), waiting time depends on the first two moments (mean and variance) of interarrival and service time distributions. Among available approaches, the Allen-Cunneen approximation is widely used due to its simplicity and robustness, and it serves as the basis for the improved KLB and Kimura formulations presented in Figure 2.

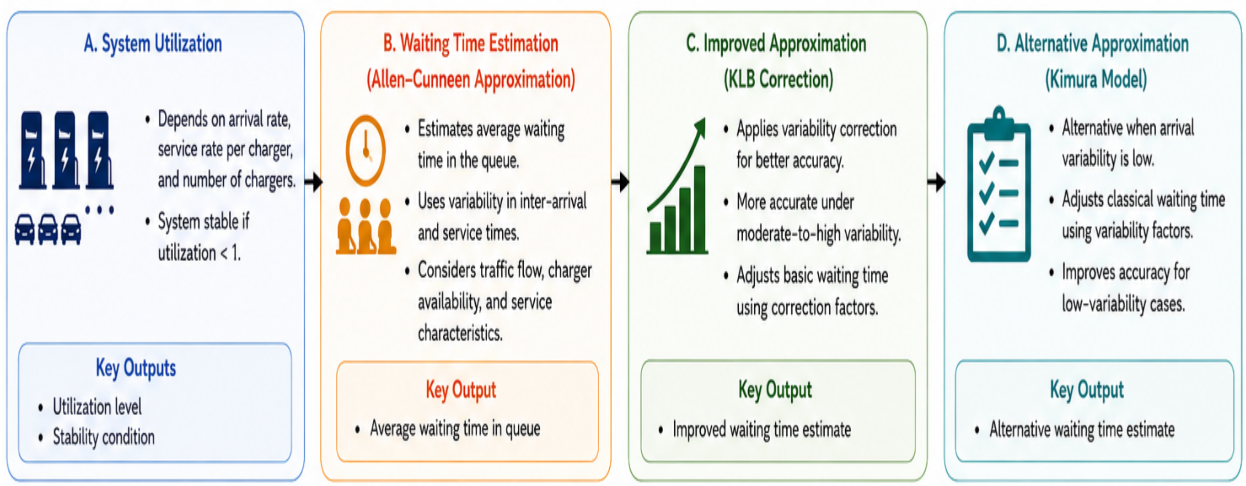

Figure 2. G/G/C Queuing Framework

The system utilization is defined as:

$$\rho = \frac{\lambda}{C\mu} \tag{13}$$

where: λ is the EV arrival rate, $\mu$is the service rate per charger, and C is the number of chargers.
System stability requires: $\rho < 1$.

Waiting Time Estimation

The average waiting time in the queue is estimated using the Allen-Cunneen approximation (Sztrik, 2012):

$$W_q = \frac{C_a^2+C_s^2}{2} \; X \; \frac{\rho^{\sqrt{2(C+1)}-1}}{C(1-\rho)} X \; \frac{1}{\mu} \tag{14}$$

$$C_a^2 = \frac{Var(\lambda)}{(\lambda)^2} \tag{15}$$

$$C_s^2 = \frac{Var(S)}{(E[S])^2} \tag{16}$$

where:
C_a= coefficient of variation of interarrival times.
C_s= coefficient of variation of service times.

Improved Approximation (KLB Correction)

To enhance accuracy, especially under moderate to high variability, the Kramer-Langenbach–Belz (KLB) correction can be applied (Sztrik, 2012):

$$W_q = \frac{C_a^2+C_s^2}{2} \; X \frac{\rho}{\mu(1-\rho)} \; X \; G_{KLB} \tag{17}$$

where the correction factor G_{KLB} adjusts for variability effects. This formulation has been shown to provide improved accuracy over the basic Allen-Cunneen approximation, particularly when variability in arrivals or service times is significant (Sztrik, 2012).

Alternative Approximation (Kimura Model)

For cases where arrival variability is relatively low $(C_a^2 < 1)$, the Kimura approximation provides an alternative(Sztrik, 2012):

$$W_q = \frac{C_a^2+C_s^2}{2} \; X \; W_q^{M/M/C} X \left[(1-C_a^2)\exp\left(\frac{2(1-\rho)}{3\rho}\right) + C_a^2\right]^{-1} \tag{18}$$

This approach improves estimation accuracy by adjusting the classical M/M/C waiting time using variability correction factors derived from simulation studies.

4. Results and Discussion

This section presents the results of the proposed framework and their implications for EV charging infrastructure planning. It integrates traffic data, stochastic EV arrival modeling, and queuing analysis to evaluate system performance under current and future demand conditions. The results highlight how traffic variability and EV adoption levels influence charging demand, peak load, and charging station efficiency.

4.1 EV Market and System Assumptions

The conversion of traffic flow into EV charging demand relies on key market and behavioral assumptions. An EV penetration rate of 3.4% (Transport Canada, 2025) and a 4% charging station capture rate are used to estimate charging demand from observed traffic flows. These are treated as scenario based planning assumptions rather than directly observed behavioral data. The EV penetration rate reflects current Canadian adoption levels, while the capture rate is adopted from prior work (Akram and Abdul-Kader, 2026). Given the cross border nature of the corridor, actual charging behavior may vary due to differences in trip purposes, vehicle origin, route choice, and charging availability; thus, these values provide a baseline for scenario analysis. The average energy demand per charging event is assumed to be 50 kWh, based on a 60 kWh battery with an 80% charging level (Akram and Abdul-Kader, 2026). Charging is assumed to occur when the battery state of charge falls below a critical threshold, reflecting realistic highway charging behavior.

4.2 Study Area and Data Description

The study is conducted at the Huron Church Road-Highway 401 in Windsor, Ontario, Canada. This corridor is a major transportation hub that accommodates urban commuter traffic, highway freight movement, and cross border flows between Canada and the United States. Its heterogeneous traffic composition and high variability make it well suited for stochastic modeling of EV charging demand.

4.3 Traffic Data Description

The dataset consists of lane level hourly traffic observations collected across seven lanes (L1-L7) over a 24-hour period. It captures temporal variations, directional flow differences, and mixed traffic conditions, enabling a realistic representation of corridor level mobility patterns.
Key characteristics include:

- Data source: Office of the City Engineer Windsor (2025)
- Spatial resolution: 7 lanes (L1-L7) capturing traffic heterogeneity
- Temporal resolution: Hourly observations over 24 hours
- Total daily traffic: 34,946 vehicles/day (Table 1)
- Average hourly flow: 1,456 vehicles/hour
- Peak flow: 2,389 vehicles/hour
- Minimum flow: 251 vehicles/hour
- Vehicle mix: Passenger and freight vehicles
- Commercial vehicle share: 8.5% (MTO, 2018)
- EV penetration rate: 3.4% (Transport Canada, 2025)
- Charging station capture rate: 4% (Akram and Abdul-Kader, 2026)
- Peak EV arrival rate: 3.25 EV/hr (Table 1).

The resulting lane-wise traffic distribution, EV arrivals, and energy demand are presented in Table 1.

Table 1. Lane Data, EV Arrivals, and Load Demand

Time	L1	L2	L3	L4	L5	L6	L7	Total Vehicles /hr	λEV(t)= Flow(t)×p(EV) ×p(capture)	Load (kWh/hr)	Load (MW)
12 AM	46	152	60	6	41	109	55	469	0.64	32	0.032
1 AM	38	112	40	2	20	78	27	317	0.43	21.5	0.022
2 AM	27	113	22	5	17	41	26	251	0.34	17.0	0.017
3 AM	30	104	33	5	12	44	30	258	0.35	17.5	0.018

Time	L1	L2	L3	L4	L5	L6	L7	Total Vehicles /hr	λEV(t)= Flow(t)×p(EV) ×p(capture)	Load (kWh/hr)	Load (MW)
4 AM	45	120	69	0	32	89	35	390	0.53	26.5	0.027
5 AM	96	191	190	4	46	148	111	786	1.07	53.5	0.054
6 AM	184	290	373	10	105	235	178	1375	1.87	93.5	0.094
7 AM	317	340	464	10	133	263	211	1738	2.36	118.0	0.118
8 AM	402	377	471	14	126	273	228	1891	2.57	128.5	0.129
9 AM	336	330	388	18	152	301	213	1738	2.36	118	0.118
10 AM	292	332	340	27	156	317	204	1668	2.27	113.5	0.114
11 AM	345	351	362	20	181	369	241	1869	2.54	127.0	0.127
12 PM	350	343	372	39	242	363	310	2019	2.75	137.5	0.138
1 PM	353	332	369	32	298	386	268	2038	2.77	138.5	0.139
2 PM	364	349	384	39	346	403	299	2184	2.97	148.5	0.149
3 PM	454	387	431	37	366	418	296	2389	3.25	162.5	0.163
4 PM	426	382	381	32	447	394	303	2365	3.22	161.0	0.161
5 PM	455	374	403	37	406	373	320	2368	3.22	161.0	0.161
6 PM	363	328	364	27	379	399	352	2212	3.01	150.5	0.151
7 PM	297	301	249	25	295	348	276	1791	2.44	122.0	0.122
8 PM	238	265	170	22	244	303	223	1465	1.99	99.5	0.100
9 PM	174	224	165	13	195	309	244	1324	1.80	90.0	0.090
10 PM	165	218	171	15	167	278	193	1207	1.64	82.0	0.082
11 PM	109	196	103	5	113	197	111	834	1.13	56.5	0.057
Total	5906	6,511	6,374	444	4,519	6,438	4,754	34,946	47.52	2376	2.38

4.4 Estimation of Daily EV Charging Demand

The daily EV charging demand is derived by converting corridor traffic flow into EV specific charging events using EV penetration and charging station capture probability. This step provides a realistic baseline for station utilization and serves as the primary input for subsequent queueing analysis.

Using the lane level traffic data, the total observed traffic volume is:

Total traffic flow = 34,946 vehicles/day

EV penetration rate = 3.4%

Charging station capture rate = 4%

The number of EVs within the traffic stream is estimated as:

$$EV_{traffic} = 34{,}946 \times 0.034 = 1{,}188.16 \text{ EVs/day}$$

Then, applying the charging station capture probability:

$$EV_{daily} = 1{,}188.16 \times 0.04 = 47.53 \text{ EVs/day}$$

Thus, the effective charging demand is:

EV daily demand = 47.52 = 48 EVs/day

These estimates are used as input for the queuing and load analysis presented in the subsequent sections, where system performance and optimal charger configuration are evaluated under varying demand levels.

4.5 Future EV Charging Demand and Load

The projected EV charging demand and corresponding electrical load under different EV penetration scenarios are summarized in Table 2.

Table 2. Future EV Charging Demand and Load Scaling by EV Penetration

Scenario	EV Share	Scaling Factor	Peak EVs/hr	Peak Load (kWh/hr)	Peak Load (MW)	Daily EV Demand
current	3.4%	1.00	3.25	162.5	0.163	48 EV/day
Scenario 1	10%	2.94	9.56	478	0.478	141 EV/day
Scenario 2	30%	8.82	28.65	1433	1.433	423 EV/day
Scenario 3	50%	14.71	47.80	2390	2.39	706 EV/day

The results indicate a substantial increase in charging demand and electrical load as EV penetration rises. Under current conditions, the system experiences a peak arrival rate of 3.25 EV/hr, corresponding to a peak charging load of 162.5 kWh/hr (0.163 MW). Under a 50% EV penetration scenario, demand increases to approximately 47.8 EV/hr, with peak load reaching 2.39 MW and daily charging demand increasing to approximately 706 EV/day, indicating significant future infrastructure and grid expansion requirements.

4.6 Queuing Model (G/G/C Framework C = 3 Design Case)

System performance is evaluated for a three-charger configuration (C = 3) to determine an efficient and stable design under peak demand conditions.

Input Parameters (Peak Condition):

Peak arrival rate: $\lambda = 3.25$ EV/hr

Average service time (15-20 minutes) (Muttaqi et al., 2023).

$$t_s = 17.5 \text{ min} = 0.292 \text{ hr}$$

Service rate per charger:

$$\mu = 1 / 0.292 = 3.42 \text{ EV/hr}$$

The variability parameters are derived from empirical traffic based EV arrival patterns (Table 1) and bounded service times 15-20 minutes (Muttaqi et al., 2023). A calibrated adjustment consistent with established queueing theory (e.g., Sztrik, 2012) is applied to capture real world variability in arrivals and charging durations. Table 3 present the results for C = 3.

Table 3. G/G/C Queue Performance (C = 3, Peak Condition)

Method	Waiting Time W_q	Total Time W
Allen-Cunneen	0.77 min	18.3 min
KLB	5.8 min	23.8 min
Kimura	1.4 min	19.9 min

The results indicate that the system operates under a stable regime with utilization reduced to approximately $\rho = 0.317$. The Allen-Cunneen approximation suggests negligible waiting time, while the KLB correction provides a more realistic estimate of about 5.8 minutes under variability effects. Even under the conservative Kimura approximation, the total system time remains below 19.9 minutes. Overall, the C = 3 configuration achieves a strong balance between service efficiency and infrastructure utilization, significantly reducing congestion while maintaining practical charger deployment under traffic driven stochastic demand.

4.7 Charging System Performance and Optimal Configuration

The EV charging system is evaluated using the G/G/C queuing framework for two configurations: C = 2 and C = 3 chargers under identical peak hour demand conditions. The results, summarized in Table 4, compare utilization, waiting time, queue length, and total system time.

Table 4. G/G/C Performance Comparison

Metric	C = 2 Chargers	C = 3 Chargers
System Utilization (ρ)	0.475	0.317

Metric	C = 2 Chargers	C = 3 Chargers
Stability Condition	Stable	Highly Stable
Service Capacity (Cμ)	6.84 EV/hr	10.26 EV/hr
Peak Arrival Rate (λ)	3.25 EV/hr	3.25 EV/hr
Allen-Cunneen Waiting Time	4.3 min	0.77 min
KLB Waiting Time	11.3 min	5.8 min
Kimura Waiting Time	6.9 min	1.4min
Total System Time (AC)	21.8 min	18.3 min
Average Queue Length	0.23 vehicles	0.04 vehicles
Performance Level	Moderate Congestion Risk	Minimal Congestion

The results show that both systems are stable; however, performance improves significantly with C = 3. The three-charger configuration reduces utilization, minimizes queue formation, and lowers waiting times across all approximation methods. Even under conservative estimates, C = 3 consistently provides better service efficiency. Overall, C = 3 is identified as the optimal configuration, offering a strong balance between infrastructure cost and operational performance under stochastic traffic-driven EV demand.

4.8 Recommendations

The transition toward electric mobility requires integrated planning across transportation systems, electrical grid operations, and charging infrastructure development. The findings of this study demonstrate that EV charging demand is highly time dependent and strongly influenced by traffic variability, with system performance significantly improving under optimized charger configurations (C = 3). Based on Table 2 results and scenario analysis, the following targeted recommendations are proposed:

- *For policymakers:* EV infrastructure planning should shift from static demand estimates to traffic driven, time varying modeling approaches that explicitly capture corridor level peak conditions. This is essential for accurate infrastructure sizing under future EV penetration scenarios reaching up to 50%, where demand may reach approximately 706 EV/day.
- *For government agencies:* Approval and planning frameworks should mandate the use of hourly traffic based demand profiles and congestion aware design criteria rather than relying on annual average traffic or simplified EV adoption assumptions.
- *For grid operators and electricity providers:* Distribution system planning should incorporate hourly EV charging load profiles derived from traffic dynamics to support transformer sizing, feeder reinforcement, and peak load management. Under high penetration scenarios, demand may increase up to 706 EV/day, requiring proactive grid upgrades.
- *For EV industry stakeholders (manufacturers and charging operators):* Charging infrastructure deployment should prioritize high traffic corridors and adopt modular designs that enable scalability from lower capacity configurations (C = 2) to optimized systems (C = 3 or higher) as demand increases.
- *For infrastructure planners and stakeholders:* Station design should explicitly account for stochastic arrival patterns and peak hour congestion. Results show that increasing capacity from C = 2 to C = 3 reduces average waiting time from 11.3 minutes to 5.8 minutes, significantly improving user experience and operational efficiency.
- *For utilities and energy planners:* Integration of renewable energy sources and energy storage systems at high demand charging stations is recommended to mitigate peak load stress and enhance grid resilience during high demand periods.
- *For collaborative planning bodies*: Effective coordination between transportation authorities, energy regulators, and private sector operators is essential to ensure alignment between mobility demand growth and electrical infrastructure expansion.
- *Key recommendation:* EV charging infrastructure planning should adopt a data-driven, integrated transportation energy framework that combines traffic flow analysis, stochastic demand modeling, and

queueing based system optimization to ensure scalability, reliability, and grid stability under future electrification scenarios.

Overall, these recommendations highlight that EV infrastructure planning must move beyond static forecasting toward integrated, data-driven decision frameworks. Such an approach ensures efficient infrastructure investment, improved charging service quality, and stable grid operation under increasingly dynamic and electrified transportation systems.

4.9 Comparative Analysis

Table 5 presents a comparative analysis between the proposed framework and existing studies in literature.

Table 5. Comparative Analysis of EV Charging Studies

Study/ Model	Traffic Integration	Arrival Process	Queueing Model	Energy System Modeling	Spatial Scope		Key Focus	Key Limitation
Soufiani et al. (2026)	No direct traffic integration	Markovian Arrival Process (MAP)	Multi-server queue (phase-type service)	Abstract service modeling	Station-level		Advanced stochastic queueing	Limited real traffic linkage
Mao et al. (2026)	Indirect (data-driven features)	ML-based prediction (RF, GBDT, LSTM, BiLSTM)	Not included	Strong predictive energy modeling	Station-level		AI-based EV demand forecasting	Lacks queueing and operational analysis
Liao et al. (2026)	Yes (mobility/spatiotemporal data)	Aggregated temporal demand	Not explicitly queue-based	System-level energy demand	City-scale		Infrastructure planning under mobility growth	No explicit service/queue performance
Masrur et al. (2025)	Not explicitly traffic-driven	Time-varying arrival rates	M/M/C, M1/M2/C	Basic load estimation	Station-level		Congestion modeling under variability	Relies on assumed stochastic arrivals
Liu (2025)	Indirect	Not explicitly modeled	Queueing-based control	Energy storage integration	Station-level		Scheduling and congestion reduction	Limited traffic-energy coupling
Pourvaziri et al. (2024)	Partial (optimization-based demand)	Assumed stochastic demand	Queueing + optimization hybrid	Implicit energy modeling	Network-level		Joint location-capacity optimization	Weak empirical validation
Meng et al. (2024)	Indirect demand assumption	Time-scheduled arrivals	M/M/s/K	Simplified energy allocation	Single station		Scheduling optimization	No traffic-based demand linkage

Study/ Model	Traffic Integration	Arrival Process	Queueing Model	Energy System Modeling	Spatial Scope		Key Focus	Key Limitation
Proposed Framework (This Study)	Yes (lane-level traffic flow integration)	Time-varying stochastic process derived from traffic λ(t)	G/G/C (AC, KLB, Kimura approximations)	Traffic-to-energy transformation (kWh, MW profiles)	Corridor-level (scalable to network)		Integrated transport–energy–queueing framework	Assumes simplified behavioral parameters; limited real charging calibration

The comparative analysis in Table 5 shows that existing studies mainly focus on isolated aspects of EV charging systems, such as demand forecasting, queueing analysis, or energy system optimization, often relying on simplified assumptions and limited integration with real traffic data. In contrast, the proposed framework provides a more comprehensive approach by directly linking lane level traffic flow with time varying stochastic EV arrivals, energy load estimation, and G/G/C queueing analysis. This integration enables a more realistic representation of charging demand and system performance, while also capturing the interaction between transportation and power systems. Overall, the proposed model offers a more unified and operationally relevant framework compared to existing fragmented approaches.

4.10 Sensitivity Analysis

A sensitivity analysis is conducted, and the results are presented in Table 6.

Table 6. Sensitivity Analysis

Parameter	Variation	Calculation Method	Key Numerical Results	Impact on System Performance	Interpretation
EV Penetration Rate p(EV)	3.4% 10% 30% 50%	EV(t) = Flow × p (EV) × p (capture)	48 EV/day 141 EV/day 423 EV/day 706 EV/day	Peak load increases from 0.163 MW to 2.39 MW	Strong increase in demand with higher EV adoption
Capture Rate p(capture)	2% 4% 8%	EV(t) = Flow × p (EV) × p (capture)	24 EV/day 48 EV/day 96 EV/day	Queue length and waiting time increase proportionally	Charging behavior strongly affects station utilization
Number of Chargers (C)	C = 2 C = 3 C = 4	$\rho = \lambda / (C\mu)$	$\rho = 0.475$ $\rho = 0.317$ $\rho = 0.238$	Waiting time decreases significantly with higher charger capacity	Increasing chargers improves system stability
Service Time (t_s)	15 min 17.5 min 20 min	$\mu = 1 / t_s$	$\mu = 4.00$ EV/hr $\mu = 3.42$ EV/hr $\mu = 3.00$ EV/hr	Higher service time increases utilization and delay	Charging speed strongly impacts queue performance

The sensitivity analysis indicates that EV penetration rate and charger capacity are the most influential parameters affecting charging demand and queue performance. Higher EV adoption and longer charging duration increase congestion and peak load, while increasing the number of chargers significantly improves system stability and reduces waiting time.

5. Conclusion

This study developed a traffic informed EV charging demand estimation framework that links observed traffic flow data with estimated EV charging demand, energy demand modeling, and queueing based performance evaluation.

Using lane level traffic data from a major transportation corridor in Windsor, Ontario, Canada, the framework successfully converted mobility patterns into EV charging demand and corresponding electrical load profiles.

The results show that under current conditions (3.4% EV penetration and 4% capture rate), the charging demand is approximately 48 EVs/day, with a peak arrival rate of 3.25 EVs/hr, corresponding to a peak traffic flow of 2,389 vehicles/hr and a peak charging load of 162.5 kWh/hr (0.163 MW). Scenario analysis demonstrates that future EV adoption can substantially increase infrastructure requirements, with demand rising to approximately 706 EVs/day and peak charging load reaching approximately 2.39 MW under a 50% EV penetration scenario. These findings highlight the strong sensitivity of charging infrastructure requirements to EV market growth.

The G/G/C queueing analysis further demonstrates that charger configuration strongly influences operational performance. Under peak demand conditions, the three-charger configuration significantly improves system efficiency compared with the two-charger configuration. Specifically, system utilization decreases from 0.475 to 0.317, while waiting time is reduced to approximately 5.8 minutes under the KLB approximation. Queue length is also substantially reduced, confirming that the C = 3 configuration provides a practical balance between infrastructure utilization and service quality/level under traffic-driven stochastic demand.

Overall, the study demonstrates that integrating transportation demand with electrical load modeling is essential for future EV infrastructure planning. By generating hourly EV charging load profiles and incorporating stochastic queueing analysis, the proposed framework supports more accurate infrastructure sizing, congestion mitigation, and grid planning. The findings confirm that static planning approaches are insufficient under rapidly evolving EV adoption trends, and that integrated transportation energy modeling frameworks are necessary for scalable, efficient, and reliable EV charging network development.

5.1 Future Work

Future research should focus on validating the proposed framework using real world EV charging station data to improve the accuracy of arrival, service, and behavioral assumptions. The model can be extended to a network level setting to capture interactions among multiple charging stations and EV rerouting behavior. More advanced stochastic processes or machine learning methods (e.g., Hawkes processes or deep learning) could be explored to better represent nonlinear and bursty demand patterns. Future work should also integrate distribution grid constraints and renewable energy considerations to enable a fully coupled transportation power system model. In addition, incorporating real-time adaptive control strategies and explicit uncertainty quantification would further improve operational efficiency and decision making robustness under high EV penetration scenarios.

References

Akram and Abdul-Kader, Designing a Sustainable Off-Grid EV Charging Station: Analysis Across Urban and Remote Canadian Regions Batteries, vol. 12, pp. 17,2026.

Alfraidi,W., Shalaby, M., Alaql, F. Modeling EV Charging Station Loads Considering On-Road Wireless Charging Capabilities. World Electric Vehicle Journal, vol. 14, pp. 313, 2023.

City of Windsor. Office of The City Engineer. Available online: https://www.citywindsor.ca/city-hall/citydepartments/ public works, 2025. (accessed on 15 September 2025).

Liao, C., Deng, J., Chen, X.M., yuan, Q. (2026) Optimizing electric vehicle charging patterns and infrastructure for grid decarbonization. Communications Sustainability, vol. 1, pp. 43, 2026.

Liu, J. Configuration of Electric Vehicle Charging Facilities Based on Queuing Theory. Theoretical and Natural Science, vol. 92, pp. 129–133, 2025.

Mao, M., Yu, X., Wang, F., Zhu, J. Electric vehicle charging demand forecasting: A data-driven integrated learning approach, Renewable Energy, vol. 256, pp. 124141, 2026.

Masrura, H., Al-Awamib, A.T. Dynamics of an EV Charging Station considering Queuing Theory. Transportation Research Procedia, vol. 84, pp. 434–439, 2025.

Meng, F., Pei, W., Zhang, Q., Zhang, Y., Ma, B., Li, L. Research on the capacity of charging stations based on queuing theory and energy storage scheduling optimization sharing strategy. Journal of Energy Storage , vol. 96, pp.112673, 2024.

Ministry of Transportation Ontario. Traffic Volume Data Report https://www.library.mto.gov.on.ca/SydneyPLUS/TechPubs/Theme.aspx?r=702797&f=files%2FProvincial+Highways+Traffic+Volumes+2019+AADT+Only.pdf&m=resource, (2019).

Muttaqi, K. M., Isac, E., Mandal, A., Sutanto, D., Akter, S. Fast and random charging of electric vehicles and its impacts: State-of-the-art technologies and case studies. Electric Power Systems Research, vol. 226, pp. 109899, 2023.

Pourvaziri, H., Sarhadi, H., Azad, N., Afshari, H., Taghavi, M. Planning of electric vehicle charging stations: An integrated deep learning and queueing theory approach. Transportation Research Part E, vol. 186, pp. 103568, 2024.

Shaat, M., Oroumchian, F., Abohaia, Z., El Barachi, M (2026) A Data-Driven Framework for Electric Vehicle Charging Infrastructure Planning: Demand Estimation, Economic Feasibility, and Spatial Equity. World Electric Vehicle Journal, vol. 17, pp. 42, 2026.

Soufiani, E., Almehdawe, E., Tang, Y. (2026). A realistic MAP/PH/c queuing model for electric vehicle charging stations: theoretical development and real-world case study. Transportmetrica B: Transport Dynamics, vol. 14(1).

Sztrik. Basic Queuing Theory. https://scispace.com/pdf/basic-queueing-theory-27qn9f8oum.pdf, 2012 (accessed on 15 April 2026).

Transport Canada. ZEV Council Dashboard. Available online: https://tc.canada.ca/en/road-transportation/innovativetechnologies/ zero-emission-vehicles/zev-council-dashboard, 2025. (accessed on 12 April 2026).

Biographies

Muhammad Nadeem Akram is a Postdoctoral Fellow in the Department of Mechanical, Automotive, and Materials Engineering, at the University of Windsor, Windsor, Ontario, Canada. He earned his PhD in Industrial and Manufacturing Systems Engineering from the University of Windsor. He holds a Master of Applied Science in Industrial Engineering and a Master of Industrial Engineering from the University of Windsor. He received his B.Sc. in Electrical Engineering from the University of Engineering and Technology, Lahore, Pakistan, and a B.Sc. in Mathematics and Physics from the University of the Punjab, Lahore, Pakistan. His research interests include sustainable manufacturing, electric vehicles, EV batteries, and renewable energy systems.

Walid Abdul Kader is a professor of Industrial Engineering in the Faculty of Engineering at the University of Windsor, Windsor, Canada. He holds a PhD degree in Mechanical Engineering from Université Laval, Québec City, Canada. He completed his bachelor's degree from Université du Québec à Trois-Rivières, Canada, and master's degree from École Polytechnique de Montréal, Canada. His research interests relate to performance evaluation of reverse logistics and manufacturing/remanufacturing systems prone to accidental failure and repair. His publications have appeared in many leading national and international journals and conferences proceedings.