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MODELING USER CHARGING BEHAVIOR IN EV NETWORKS USING M/M/N QUEUEING SYSTEMS

Introduction. The rapid growth of electric vehicles has increased the variability and peakiness of charging demand, producing local congestion, waiting times, and unstable station utilization. Demand is often synchronized by daily routines and travel patterns, and spatial imbalances in station availability amplify these effects in urban networks [1-4]. Evidence from empirical studies shows that user routines and charging preferences generate heterogeneous arrival processes and service times, which must be considered to ensure reliable access to charging services [9-12].

Analysis of recent research and publications. Recent forecasting and grid-impact studies predict charging loads using travel- and context-aware models, including Bayesian and transformer-based methods, but they mostly operate on aggregated demand and rarely translate predictions into service-level congestion metrics [2; 5-8].

Behavior-focused analyses based on high-resolution session datasets, clustering, and functional data methods demonstrate pronounced heterogeneity: habitual workplace users and long-duration sessions can dominate charger occupancy, while other users rely on short fast-charging sessions [9-12].

Queueing theory provides analytical tools for station planning and congestion evaluation; multi-server models and finite-queue formulations have been applied to infrastructure planning, routing, and performance evaluation under strategic user choices [13-18]. However, most queueing approaches assume homogeneous users and do not map empirically derived behavioral segments to queue parameters (λ, μ, ρ), leaving the stability implications of behavioral composition underexplored [12-14; 19].

Therefore, integrating behavioral segmentation with multi-server queueing models is necessary to identify which user groups generate congestion and to inform targeted managerial interventions in innovative charging services.

Purpose of the article. The purpose of this article is to quantify how distinct EV charging behavior segments affect the performance of multi-server charging stations modeled as M/M/n queueing systems, focusing on arrival intensity (λ), service rate (μ), utilization (ρ), and expected waiting time in queue (Wq).

Research results. Understanding the diversity of electric vehicle (EV) user behavior is essential for developing accurate demand models in charging infrastructure. To capture this behavioral heterogeneity, a data-driven segmentation analysis was performed using unsupervised machine learning. The objective was to identify homogeneous behavioral groups of EV users based on their actual charging patterns.

The raw dataset included historical records of charging sessions collected over a multi-week period, with each observation representing one user session. To build meaningful behavioral profiles, the following features were selected:

- hour_start – start time of charging session (in hours),
- duration_h – duration of charging (in hours),
- energy_kWh – total energy transferred (kWh),
- avg_power – average charging power (W),
- price_per_kWh_fixed – fixed electricity cost per kWh (UAH),
- station_type – type of charging station (Alternating Current (AC) or Direct Current (DC)),
- is_weekend – binary weekend indicator.

Numerical variables were standardized using StandardScaler to ensure equal scaling and eliminate unit-based distortions. Categorical variables (station_ type and is_weekend) were encoded using One-Hot Encoding, allowing the clustering algorithm to treat binary inputs effectively. Additionally, outliers in price (above the 99.5th percentile) were removed to increase robustness, and missing values were confirmed absent.

The k-means clustering algorithm was selected due to its simplicity, efficiency, and interpretability in high-dimensional behavioral datasets. The optimal number of clusters k was determined using two metrics:

- the Elbow Method, which analyzes the total within-cluster sum of squares (SSE), and
- the Silhouette Score, which measures separation quality between clusters.

Both methods consistently pointed to k = 4 as the most appropriate choice (Figure 1, Figure 2). The silhouette coefficient reached a maximum of 0.247, indicating moderate but stable cluster separability – typical for behavioral data with overlapping patterns.

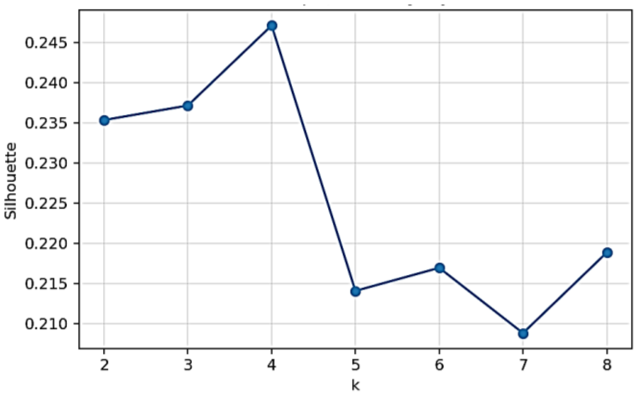

Fig. 1. **Silhouette scores vs. number of clusters (k)**
Source: compiled by the authors

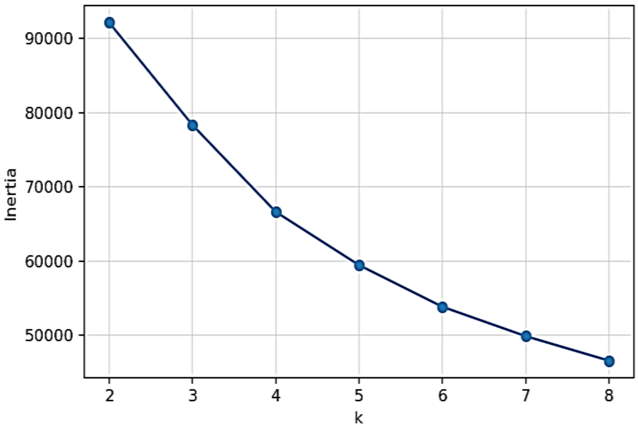

Fig. 2. **Elbow Method Plot (SSE vs. k)**
Source: compiled by the authors

Dimensionality reduction was performed using Principal Component Analysis (PCA) to visualize cluster distribution in two-dimensional space (PC1, PC2). The results showed four relatively compact and distinct clusters, with minor overlap (Figure 3).

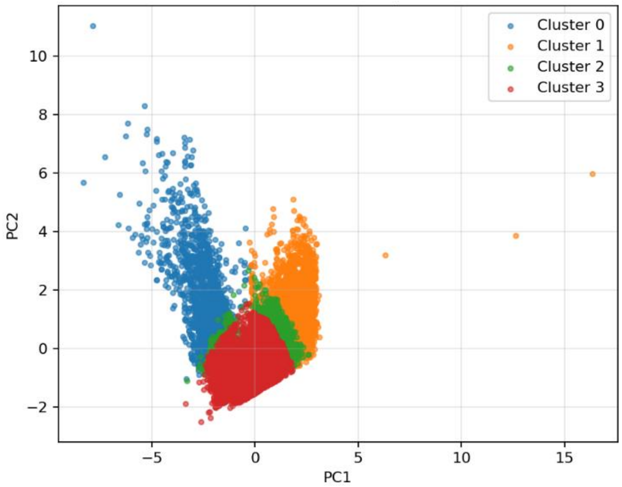

Fig. 3. **PCA visualization of the 4 clusters**
Source: compiled by the authors

To interpret the clusters, average values of key features were calculated for each group. The profiles are presented in Table 1.

Table 1. **Cluster Centroids: Average Charging Characteristics by Segment**

Segment	hour_start	duration_h	energy_kWh	avg_power (W)	price_per_kWh (UAH)	share_AC	share_DC
0	13.97	5.47	28.44	5,626	11.96	0.98	0.02
1	12.09	0.65	34.37	61,367	14.59	0.00	0.99
2	13.04	0.78	13.58	24,752	12.88	0.18	0.82
3	12.82	0.72	11.81	23,010	12.83	0.20	0.80

Source: compiled by the authors

Each segment reflects a typical behavioral scenario:

Segment 0 – Long daytime AC sessions: Characterized by long charging durations (>5 hours), low power output, and strong preference for AC charging. Typical use case includes home or workplace parking. Users are motivated by convenience and stable vehicle availability during the day.

Segment 1 – Fast commercial DC charges: Short-duration, high-power sessions at fast-charging public stations. These users prioritize time efficiency and are willing to pay more for faster charging. Commonly associated with business travel or professional drivers.

Segment 2 – Opportunistic urban DC top-ups: Medium-power, short-duration sessions that suggest casual recharging behavior during errands. Users seek partial energy restoration without full battery replenishment.

Segment 3 – Routine workplace DC sessions: Consistent, short and moderately powerful sessions performed at regular times, suggesting habitual charging behavior. These sessions likely belong to fleet or corporate EV users with scheduled operations.

To ensure robustness, the clustering algorithm was executed five times with different initialization seeds (random_state = 1, 42, 123, 999, 2025). In all cases, the silhouette score remained unchanged (0.219 ± 0.000), confirming solution stability. Additional validation was performed using Calinski-Harabasz Index (3587.31) and Davies-Bouldin Index (1.364). Both metrics confirm acceptable intra-cluster compactness and inter-cluster separation.

To evaluate the operational performance of EV charging infrastructure, we developed a formal queueing-based analytical model grounded in M/M/c theory. The model allows for quantifying key efficiency indicators such as station load factor (ρ), average queue waiting time (W_q), queueing probability (P_w), and the average number of users in the system (L), across various demand and infrastructure scenarios.

The charging network is modeled as a collection of independent service locations, each hosting one or more charging stations with heterogeneous connector types (e.g., Type 2, CCS, CHAdeMO). Each location L acts as a spatial service node, where users arrive according to a Poisson process with a behavior-driven intensity λ.

A key structural aspect is that the number of effective service channels (c) at each location does not always equal the number of physical connectors, due to hardware constraints (e.g., two outlets sharing one power module). Therefore, for each location-connector pair, we define a subsystem, modeled as an M/M/c queue, where:

Users arrive randomly (Poisson λ),

Service time follows an exponential distribution (μ),

There is an infinite queue buffer.

Each subsystem is defined by the tuple (L, k), where:

L: Location identifier,

k: Connector type,

$c_{L,k}$: Effective number of parallel service channels,

$\lambda_{L,k}$: Arrival rate of charging sessions,

$\mu_{L,k}$: Service rate (inverse of average session duration).

Thus, each pair (L, k) is modeled as a queueing system of type M/M/c, where the arrival process follows a Poisson distribution, and the service time follows an exponential distribution.

For the stationary state of the system, the following key formulas are used:

Effective number of service channels

$$c_{L,k} = \begin{cases} \text{number of connectors of type } k, \mathit{if\ all\ can\ operate\ simultaneously}; \\ 1, \mathit{if\ the\ ports\ are\ mutually\ exclusive}. \end{cases} \quad (1)$$

That is, if two ports (CCS and CHAdeMO) share a single power module, then for the model this corresponds to one service channel ($c_{L,k} = 1$).

Arrival intensity

$$\lambda_{L,k} = \frac{N_{L,k}}{T_{obs}}, \quad (2)$$

where: $N_{L,k}$ – number of charging sessions of type k at location L during the observation period; T_{obs} – duration of the observation period in hours.

If the data have sufficient temporal granularity, the arrival rate can be represented as a time-dependent function $\lambda_{L,k}(t)$, reflecting daily and weekly demand fluctuations.

Service intensity

$$\mu_{L,k} = \frac{1}{\bar{\bar{T}}_{L,k}}, \quad (3)$$

where: $\bar{\bar{T}}_{L,k}$ – average charging duration for this connector type at location L.

This indicator reflects the average throughput capacity of one service channel.

Formally, the system is modeled as a stochastic process $N(t)$, which describes the number of requests in the system (waiting and being serviced) at time t.

The set of possible states is:

$$S = \{0,1,2, \dots\}, \quad (4)$$

where state $n \in S$ indicates that n users are simultaneously present in the system.

The number of occupied connectors in state n is $\min(n, c)$.

The process $N(t)$ is a Markov birth-death process. Transitions occur only between adjacent states:

Transition n → n + 1 (arrival of a new user) with intensity λ;

Transition n → n − 1 (departure of a user) with intensity:

$$\mu_n = \min(n, c)\, \mu, \quad (5)$$

where n – number of users currently in the system; c is the number of available service channels; $\min(n, c)$ represents the number of channels that are actively serving users at state n; μ – service rate of a single channel.

Such a structure corresponds to the classical M/M/c model with an infinite queue.

The dynamics of state probabilities are described by Kolmogorov-Chapman Equations:

$$\frac{dP_n(t)}{dt} = \lambda P_{n-1}(t) - (\lambda + \mu_n) P_n(t) + \mu_{n+1} P_{n+1}(t), \quad n \geq 0, \quad (6)$$

where $P_n(t)$ is the probability that the system is in state $n$at time t; λ is the arrival rate; μ_n is the total service rate when the system is in state n; μ_{n+1} is the total service rate when the system is in state $n + 1$; $\lambda P_{n-1}(t)$ represents transitions into state n due to new arrivals; $(\lambda + \mu_n) P_n(t)$ represents transitions out of state n; $\mu_{n+1} P_{n+1}(t)$ represents transitions into state $n$due to service completions from state $n + 1$.

Based on parameters $\lambda_{L,k}$, $\mu_{L,k}$, $c_{L,k}$, the main operational characteristics of the M/M/c system can be computed.

System Load Factor

$$\rho_{L,k} = \frac{\lambda_{L,k}}{c_{L,k}\mu_{L,k}}, \qquad (7)$$

which shows the share of time service channels of type k at location L remain occupied.

$\rho_{L,k} < 1$the system is stable; if $\rho_{L,k} \to 1$, queues emerge.

Probability of Idle System

$$P_{0,L,k} = \left[\sum_{n=0}^{c_{L,k}-1} \frac{\left(\frac{\lambda_{L,k}}{\mu_{L,k}}\right)^{n}}{n!} + \frac{\left(\frac{\lambda_{L,k}}{\mu_{L,k}}\right)^{c_{L,k}}}{c_{L,k}!\left(1-\frac{\rho_{L,k}}{c_{L,k}}\right)}\right]^{-1}, \qquad (8)$$

Probability of Waiting (Queueing Probability)

$$P_{wait,L,k} = \frac{\left(\frac{\lambda_{L,k}}{\mu_{L,k}}\right)^{c_{L,k}}}{c_{L,k}!\left(1-\frac{\rho_{L,k}}{c_{L,k}}\right)} P_{0,L,k}, \qquad (9)$$

Average Queue Length

$$L_{q,L,k} = \frac{P_{wait,L,k} * \rho_{L,k}}{\left(1-\frac{\rho_{L,k}}{c_{L,k}}\right)}, \qquad (10)$$

Average Waiting Time in Queue

$$W_{q,L,k} = \frac{L_{q,L,k}}{\lambda_{L,k}}, \qquad (11)$$

Average Time in System

$$W_{q,L,k} = \frac{L_{q,L,k}}{\lambda_{L,k}}, \qquad (12)$$

Average Number of Users in System

$$L_{L,k} = \lambda_{L,k} W_{L,k}, \qquad (13)$$

Using data from charging sessions, M/M/c characteristics were computed for every location-connector-behavioral segment combination.

Calculations were performed for five locations, each containing different types of connectors, as well as for the four behavioral segments identified earlier:

Long Daytime (AC) – long daytime AC sessions;

Planned Weekends – regular planned charging at predictable hours;

Regular Urban – short weekday sessions with consistent repetition;

Fast Commercial (DC) – short high-power DC sessions by commercial users.

Results and discussion. The M/M/c queueing framework was applied to evaluate operational performance across five charging locations, three connector types, and four behavioral user segments. The goal of the analysis is to determine how differences in arrival intensity (λ), service rate (μ), and number of service channels (c) shape queueing outcomes, including the load factor (ρ), probability of waiting (Pw), average queue length (Lq), and waiting time (Wq). Since user behavior is a major driver of temporal and structural variability in EV charging demand, the results highlight not only technical bottlenecks but also behavioral sources of instability in the system.

Figure 4 illustrates the nonlinear relationship between system utilization (ρ) and the resulting average waiting time (Wq) across all behavioral segments. As expected for an M/M/c queue, most segment-location combinations fall within the stable operating region where ρ remains well below 1, producing waiting times close to zero. This is particularly evident for the Regular Urban, Planned Weekend, and Fast DC segments, which cluster tightly near the origin of the plot. These segments demonstrate that even with moderate arrival intensities, sufficiently high service rates (μ) and short charging durations prevent queue buildup. Their results form a nearly horizontal band close to , indicating that users experience almost immediate access to chargers.

SUM of Wq	segment			
Location	Long Daytime (AC	Planned Weekend	Regular Urban	Fast Commercial (DC)
1	0.105	0.012	0.025	0.042
2	0.150	0.044	0.102	0.036
3	3.348	0.035	0.058	0.000
4	0.020	0.014	0.028	0.001
5	0.011	0.011	0.015	0.000

Fig. 4. **Heatmap of average waiting time W_q for all segment-location combinations**
Source: compiled by the authors

However, one segment exhibits substantially different behavior. The *Long Daytime (AC)* points extend far upward on the Wq axis, creating a visible vertical spread that reflects significant queueing delays. This pattern emerges even at moderate utilization values, showing that AC charging – with its inherently low service rate – approaches the instability threshold much faster than DC charging. As ρ moves toward 0.9, Wq increases sharply, consistent with the theoretical curve where waiting time grows superlinearly as the system approaches saturation. This validates the analytical prediction that long, overlapping daytime AC sessions are the primary drivers of congestion, whereas short, high-power DC sessions rarely generate any queueing pressure.

Figure 5 provides a complementary view by examining the distribution of waiting times across the four behavioral user segments. Three segments – *Regular*

Urban, *Planned Weekend*, and *Fast DC* – show extremely compact boxplots with minimal variance and median waiting times effectively equal to zero. Such narrow distributions imply highly predictable performance and consistent instantaneous service. Even when variability exists in arrival rates, short charging durations and relatively high service rates result in rapid turnover, ensuring stable operation of these subsystems across all locations.

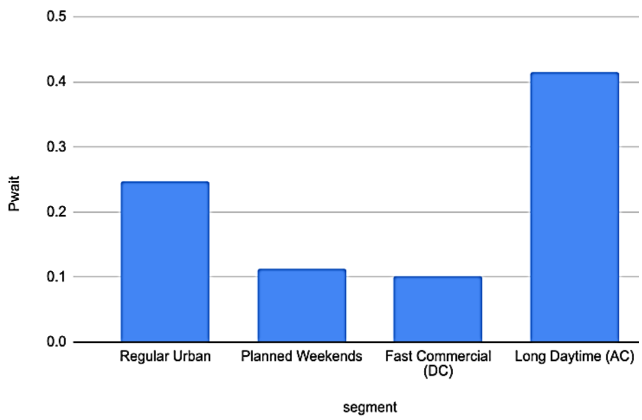

Figure 5. **Probability of waiting per segment**
Source: compiled by the authors

In contrast, the *Long Daytime (AC)* segment exhibits a distinctly different profile. Its boxplot displays a visibly elevated median, a wide interquartile range, and several extreme outliers. This shape indicates substantial variability in user experience: while some AC sessions occur during low-demand periods with minimal waiting, many fall into peak daytime windows where demand clusters and prolonged session durations cause queues to accumulate. The spread of Wq values, including the appearance of high outliers, reflects the system's sensitivity to synchronized user behavior and long occupancy of AC ports. This validates the hypothesis that AC infrastructure is more susceptible to localized congestion due to slow service rates and habitual charging patterns.

Figure 6 compares three fundamental parameters of the queueing model – arrival intensity (λ), service rate (μ), and utilization (ρ) – across behavioral segments. This figure helps explain why some segments generate queues while others remain consistently stable. The results show a clear structural divergence. The Long Daytime (AC) segment demonstrates the lowest service rate due to long charging durations typical for workplace or home-like AC sessions. Even though its arrival rate is not the highest among the segments, the combination of low and shared AC ports causes the utilization to approach 1 more quickly than in other segments. This high utilization mathematically implies that the system operates near saturation, which explains the disproportionately high waiting times observed earlier.

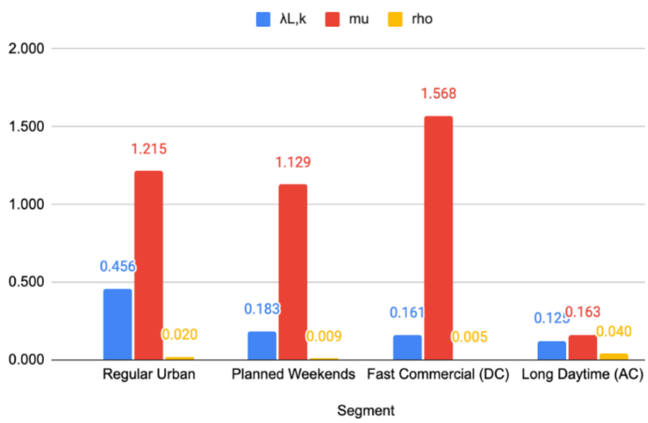

Figure 6. **Comparative bar chart of *λ*, *μ*, and *ρ* across segments**
Source: compiled by the authors

Conversely, the *Fast DC* segment exhibits the highest μ by a wide margin: DC charging sessions are short and have predictable turnover, which drastically reduces ρ even when arrival rates are substantial. The *Regular Urban* and *Planned Weekend* segments fall between these extremes. Both demonstrate moderate λ and relatively high μ, resulting in utilization levels far below the instability threshold. These results highlight that μ **is the dominant driver of system stability**: segments with high service rates naturally suppress queue formation, regardless of load intensity.

Figure 7 provides a deeper exploration of the nonlinear relationship between utilization (ρ) and average waiting time (Wq). This scatterplot visualizes an essential theoretical property of M/M/c queues: waiting times remain nearly zero until the system approaches high utilization, after which increases sharply and nonlinearly. Most data points – representing Regular Urban, Planned Weekend, and Fast DC – cluster tightly around the bottom-left region of the chart, where both ρ and remain low. This demonstrates that, for the majority of segment-location combinations, the charging infrastructure operates with substantial spare capacity and minimal queueing.

The *Long Daytime (AC)* segment again diverges from the general pattern. Its points form a distinctive upward curve that reflects the classical «blow-up» behavior of queueing systems as ρ approaches 1. Even small increases in utilization produce disproportionately large waiting times. This pattern is consistent with analytical results and confirms that the instability observed at some AC locations is not random but structurally inherent to the combination of long sessions, synchronized user behavior, and limited AC charging throughput. The fact that no other segment displays this curve demonstrates that DC infrastructure, due to its fast turnover, effectively decouples high utilization from high delays.

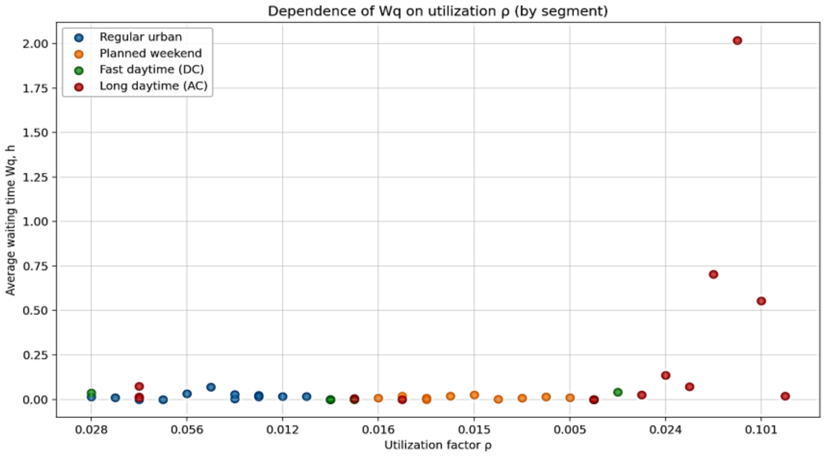

Fig. 7. **Scatterplot ρ vs W_q**
Source: compiled by the authors

The nonlinear shape in Figure 4 empirically validates queueing theory predictions: only the *Long Daytime (AC)* segment reaches utilization levels where waiting time increases explosively, while all other segments remain far from the instability region.

Figure 8 examines the distribution of average waiting times (Wq) across segments, providing an intuitive representation of both central tendency and variability. Three segments – Regular Urban, Planned Weekend, and Fast DC – again show extremely tight distributions with medians at or close to zero. Their interquartile ranges are minimal, and whiskers extend only slightly, indicating that queueing is essentially absent across all locations for these user groups. This stability aligns with earlier findings: short charging durations (high), predictable patterns, and sufficient connector capacity absorb variability in arrival patterns.

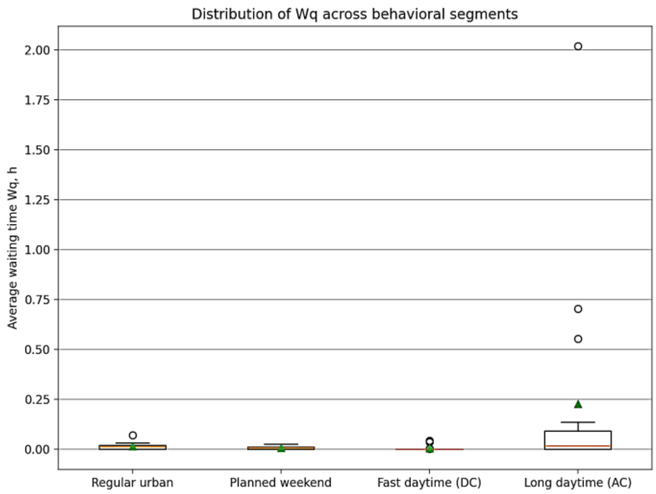

Fig. 8. **Boxplot of W_q by segment**
Source: compiled by the authors

In contrast, the boxplot for *Long Daytime (AC)* is notably different. It presents a noticeably elevated median, a wider spread, and visible outliers that reach significantly higher waiting times. This distribution reflects substantial heterogeneity in user experience – some sessions occur with no delay, while others face multi-hour waiting times. Such variability arises because long AC sessions magnify the effects of even moderate fluctuations in arrival intensity. When multiple users arrive in similar time windows, AC connectors quickly become saturated, producing queueing bursts that manifest as high-value outliers. The width of this distribution highlights that not only is this segment more likely to experience delays, but also that these delays are far less predictable.

Figure 9 illustrates how different behavioral segments contribute to the overall demand at each charging location. The distribution is highly uneven: every location exhibits its own behavioral profile, which directly shapes its sensitivity to queue formation. Locations where demand is dominated by *Regular Urban* and *Fast DC* sessions remain stable because these segments are characterized by high service rates and short charging durations, which prevent utilization from approaching critical levels.

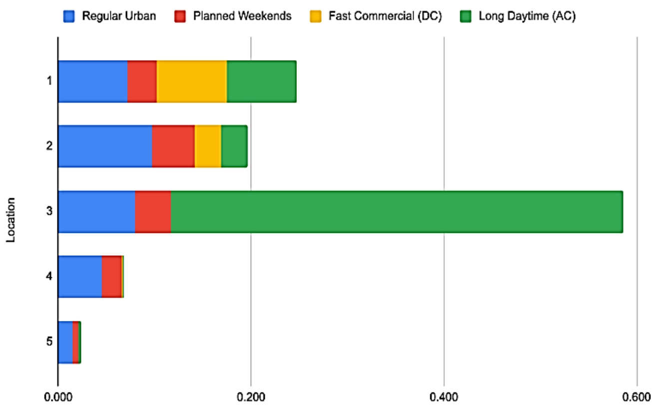

Fig. 9. **Stacked bar chart of segment load composition**
Source: compiled by the authors

In contrast, Location 3 stands out due to a disproportionately large share of Long Daytime (AC) demand.

This segment, previously shown to have very low service rates (μ) and long, overlapping daytime sessions, occupies AC ports for extended periods. As a result, even moderate arrival intensity leads to high utilization and queue buildup. The stacked bar makes this structural imbalance visually explicit: congestion at this location is not due to excessive overall traffic, but due to the dominance of a slow-turnover behavioral segment.

Importantly, some other locations experience similar or even higher total load but remain queue-free because their demand composition includes a larger share of high-turnover DC sessions. This demonstrates that queueing risk depends less on the total arrival rate (λ) and far more on the behavioral mix that determines effective service rate (μ)

To evaluate the robustness of the analytical M/M/c results and verify whether the theoretical assumptions adequately describe real operational behavior, a discrete-event simulation was conducted for all segment-location combinations. The simulation reproduced the same arrival rates (λ) and service rates (μ) computed from empirical charging data, while the number of servers (c) corresponded to the number of available connectors of each type. The simulated system followed a classical event-driven architecture: arrivals were generated according to a Poisson process, service times were sampled from an exponential distribution using empirical averages, and queue evolution was tracked over a large time horizon to ensure statistical convergence. This procedure mirrors standard validation practices in queueing theory and enables comparison between analytical predictions and dynamic system behavior under stochastic variability.

The simulation yields results highly consistent with the theoretical model. For the Regular Urban, Planned Weekend, and Fast DC segments, simulated indicators such as waiting probability (Pw), waiting time (Wq), queue length (Lq), and total number of users in the system (L) nearly coincide with their analytical values, typically differing by less than 1-3% (Figure 10). This close alignment demonstrates that the exponential service-time assumption is reasonably accurate for shorter, more homogeneous charging sessions. It also confirms that the infrastructure in these segments operates in a stable region (well below 1), where analytical queueing formulas reliably approximate real-world behavior.

The *Long Daytime (AC)* segment presents a more complex case. Here the simulation still generally agrees with analytical predictions, but deviations become larger (5-10%), particularly when utilization approaches the instability threshold. Such discrepancies are expected: when ρ nears 1, even small stochastic fluctuations in arrivals or service durations cause disproportionately large changes in waiting time, a well-known effect in heavy-traffic queueing regimes. Importantly, both simulation and theory identify the same structural phenomenon: only the AC daytime segment produces significant congestion, while all other segments remain stable. The simulation therefore reinforces the core conclusion of the analytical model – the queueing delays observed in the system are not artifacts of mathematical assumptions, but genuine operational risks arising from behavioral charging patterns.

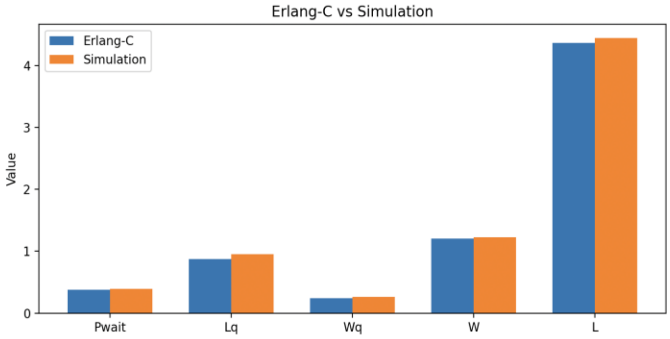

Fig. 10. **Comparison of theoretical vs simulated indicators**
Source: compiled by the authors

Overall, the simulation validates the applicability of the M/M/c framework to EV charging infrastructure and strengthens the empirical credibility of the analytical findings. It confirms that theoretical predictions offer a reliable approximation of real-world performance under typical conditions, while also accurately capturing the nonlinear growth of delays in segments with low service rates and synchronized user behavior

Conclusions. This study demonstrates that the operational performance of EV charging infrastructure is strongly shaped by behavioral heterogeneity among users and cannot be fully understood through technical parameters alone. By integrating empirical charging data with an M/M/c queueing framework, the analysis reveals that most behavioral segments – particularly Regular Urban, Planned Weekend, and Fast DC – operate in a stable regime characterized by low utilization, minimal waiting times, and predictable performance. These segments benefit from short charging durations and high service rates, which allow the system to absorb variability in arrival patterns without creating congestion.

In contrast, the Long Daytime (AC) behavioral segment exhibits fundamentally different dynamics. Its long, overlapping daytime charging sessions produce low service rates and higher utilization, which collectively push specific locations toward the saturation threshold where waiting times increase nonlinearly. Heatmaps, scatterplots, and distributional analyses consistently show that queueing delays in the network are not widespread but concentrated in a structurally distinct subset of the system. The simulation results further validate these findings, confirming that the analytical predictions remain accurate under stochastic variability and that observed instabilities are inherent to user behavior rather than artifacts of the model.

Overall, the results highlight the importance of incorporating behavioral segmentation into the planning and management of EV charging networks. Infrastructure bottlenecks arise not from overall demand volume, but from the behavioral composition of that demand – particularly the prevalence of long AC charging sessions at specific locations. These insights suggest that targeted interventions, such as redistributing AC capacity, introducing time-of-use pricing, or redefining workplace charging policies, may be more effective than uniform infrastructure expansion. By linking behavioral patterns with queueing performance, this study provides a foundation for more efficient, user-centered planning of EV charging systems and offers a methodological framework that can be extended to other mobility contexts.

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Mazhara G., Parkhomuk A. Modeling user charging behavior in EV networks using M/M/n queueing systems

EV charging networks face congestion due to behavior-driven demand. Using k-means segmentation of real sessions, an M/M/n multi-server queueing model, and discrete-event simulation, the study shows that three user segments remain stable with near-zero waiting times, while long daytime AC sessions drive utilization to 0.88–0.94 and increase expected waiting to 70–120 minutes. The results indicate that managing the behavioral mix of demand is more effective than uniform capacity expansion. across charging locations.

Keywords: electric vehicle charging, queueing system, congestion, behavioral segmentation, k-means, discrete-event simulation.

Мажара Г. А., Пархомук А. І. Моделювання поведінки користувачів під час заряджання електромобілів на основі M/M/n-систем

Швидке зростання електромобільності посилює нерівномірність та поведінково зумовлений характер попиту на заряджання, що створює операційну нестабільність, яку неможливо пояснити лише технічними параметрами обладнання. Метою дослідження є оцінювання того, як різні поведінкові групи користувачів впливають на ефективність роботи зарядних станцій за умови їх подання як багатоканальних систем масового обслуговування. Методологія поєднує сегментацію реальних сесій заряджання з використанням кластеризації k-means з аналітичним моделюванням M/M/n та дискретно-подієвим моделюванням. Результати показують, що три групи з короткими або помірними тривалостями сесій працюють у стабільному режимі: завантаження залишається низьким, а час очікування практично дорівнює нулю. Натомість сегмент тривалих денних сесій на зарядних пристроях змінного струму формує систематичні черги в різних локаціях: подовжена тривалість обслуговування та синхронізовані денні прибуття підвищують завантаження з 0,62–0,74 до 0,88–0,94 і спричиняють нелінійне зростання очікуваного часу в черзі до 70–120 хвилин у режимах наближення до насичення. Результати симуляції підтверджують аналітичні оцінки (відхилення менше 5% у стабільних режимах) і демонструють, що формування черг визначається поведінковими патернами, а не загальним обсягом попиту. Практична цінність полягає в обґрунтуванні управлінських інструментів, які змінюють поведінковий склад попиту та перенаправляють повільне заряджання, що може бути ефективнішим за механічне нарощування фізичної потужності інфраструктури. Наукова новизна дослідження полягає у прямому відображенні емпірично виділених поведінкових сегментів у параметрах системи масового обслуговування (інтенсивність надходжень, інтенсивність обслуговування та коефіцієнт завантаження), що дозволяє ідентифікувати джерела перевантаження та формувати цільові рішення для операторів зарядної інфраструктури й органів управління міською мобільністю.

Ключові слова: заряджання електромобілів, черги, багатоканальні системи, сегментація поведінки, k-means, дискретно-подієве моделювання.