Modelling the Transient Evolution of Queues in Plugged-in Electric Vehicles(PEV) Fast Charging Stations

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Abstract. The transportation sector is responsible for approximately 23% of global greenhouse gas (GHG) emissions, with road transportation contributing nearly 70% of these emissions. The widespread adoption of electric vehicles (EVs) is transforming this sector by reducing emissions and decreasing reliance on fossil fuels. However, the growing number of EVs presents significant challenges for charging infrastructure, particularly in managing long queues, extended wait times, and limited station capacity. Most existing studies on the performance of electric vehicle charging stations assume Poisson arrivals and exponential charging times, simplifications that often overlook real-world variability. This paper introduces a generalized queueing model that leverages empirical interarrival and charging duration data for more accurate performance evaluation. A transient analysis is conducted, examining two operational optimization strategies aimed at minimizing queue sizes during peak demand: (1) a queue management policy that encourages charging only up to a predefined state-of-charge (SoC) threshold instead of the typical 80˘100%, and (2) dynamic control of the number of active charging ports based on demand. The results show that these operational optimization policies improve the efficiency of the charging station and significantly improve the customer experience.

Keywords: Plugged-in Electric Vehicles (PEV) · Fast Charging Stations · diffusion approximation models · Transient analysis · Performance Evaluations.

1 Introduction

The transportation sector contributes approximately 23% of global greenhouse gas (GHG) emissions, with road transportation accounting for nearly 70% of these emissions [1]. The rapid adoption of electric vehicles (EVs) is driven by the urgent need to reduce the carbon footprint of transportation, a crucial step in

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mitigating pollution and other environmental challenges associated with fossil fuel consumption. As a result, plug-in electric vehicles (PEVs) are becoming an integral part of the global transportation system, with their market penetration expected to increase significantly in the coming years.

Municipalities and businesses are accelerating the shift to electric vehicles (EVs) by integrating them into fleets and offering adoption incentives. Interest among individual car owners is also rising globally, driven by the significant benefits of EVs. However, this growing demand requires a corresponding expansion of charging infrastructure and power distribution networks to ensure reliable and efficient EV operation.

Despite their environmental and economic advantages, EVs face challenges such as limited driving range and long charging durations, which can deter widespread adoption [2]. Extended charging times often lead to congestion at charging stations, particularly during peak hours, resulting in delays and reduced user satisfaction [3]. Addressing these challenges requires efficient queue management strategies that account for the stochastic nature of EV arrival patterns and charging durations.

Most existing studies on EV charging station performance assume that EV arrivals follow a Poisson process and that charging times are exponentially distributed. Consequently, the widely used queueing model for charging station analysis is the M/M/c model [3]. However, these Markovian assumptions do not always hold in real-world scenarios, necessitating more generalized models to capture system dynamics accurately. While some studies have incorporated time-varying interarrival rates [4], they remain constrained by Poisson arrival assumptions and exponential service times. An attempt to model a charging station considering non-stationary arrival and charging rates was discussed in [5].

This paper presents a diffusion-based G/G/c/N queueing framework to analyze the performance of EV charging stations under realistic, time-varying arrival rates. Using real-world data, the model captures dynamic fluctuations in customer arrivals and service times, allowing the evaluation of two operational strategies: dynamically limiting the final state of charge (SoC_f) and adjusting the number of active charging ports. Simulation results demonstrate that these strategies can effectively reduce queue lengths during peak hours, offering practical insights for optimising charging infrastructure operations.

2 Time-dependent queueing model for the fast charging station

We model the fast-charging station as a $G/G/c/N$ queue, where $N = c + K$. The notation $G/G/c/N$ indicates that both interarrival and service times follow general distributions. To capture the dynamic evolution of the number of electric vehicles (EVs) in the charging station, we approximate the system using a diffusion process. Specifically, we define a continuous process $\{X(t)\}$, where the probability of having x EVs in the station at time t is given by $\text{Prob}\{X(t) = x\}$

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for $x \in [0, N]$. These types of models were started in computer science by a single server G/G/1/N model [6]. The approach to solve diffusion equations in the case of transient states was proposed for the G/G/1/N model in [7]. We use this approach in many applications, e.g. modelling transient behaviour of SDN networks [8] and energy storage systems [9].

The following partial differential equation describes the diffusion process governing the number of EVs in the charging station, e.g. [10]:

$$\frac{\partial f(x,t;x_0)}{\partial t} = \frac{\alpha}{2}\frac{\partial^2 f(x,t;x_0)}{\partial x^2} - \beta\frac{\partial f(x,t;x_0)}{\partial x}, \tag{1}$$

where βdt and αdt represent the mean and variance of the changes in the diffusion process over an infinitesimal time interval dt. The probability density function (PDF) of the number of EVs in the charging station is given by:

$$f(x,t;x_0) = P[x \leq X(t) < x + dx \mid X(0) = x_0], \tag{2}$$

where x_0 is the initial state of the process at $t = 0$.

The mean change in the number of EVs in the charging station, β, and its variance, α, depend on the mean arrival rate λ, the squared coefficient of variation of the interarrival time C_A^2, the mean charging rate per port μ, and the squared coefficient of variation of the charging time C_B^2. They also depend on the number of currently occupied charging ports. That means that diffusion parameters depend on the process value. To represent it in an easy form, the diffusion interval $[0, N]$ is partitioned into c sub-intervals: $[0,1],[1,2],\dots,[c-1,N]$. Each sub-interval corresponds to a specific number of occupied charging ports at a given time, from one to c. In the last sub-interval, $[c-1, N]$, all c charging ports are occupied.

The diffusion parameters for each sub-interval are chosen as

$$\begin{aligned}
&\alpha_i = \lambda C_A^2 + i\mu C_B^2, \quad \beta_i = \lambda - i\mu \quad \text{for } i-1 < x < i, \quad i = 1,2,\dots,c-1 \\
&\alpha_c = \lambda C_A^2 + c\mu C_B^2, \quad \beta_c = \lambda - c\mu \quad \text{for } c-1 < x < N
\end{aligned} \tag{3}$$

The state of the diffusion process, x, evolves as EVs arrive at the charging station, begin charging when a port becomes available, and depart upon completing their charge. Probability mass shifts between neighboring sub-intervals whenever the charging ports are not fully occupied and EVs enter or exit the system.

The probability density function (PDF) of the number of EVs in the station is constructed from the diffusion process PDFs across all sub-intervals. These are obtained by solving the diffusion equations for each sub-interval, incorporating the probability flows between adjacent regions as described in [11].

The application used to solve the system is implemented in Python and executed on an HP ProLiant DL580 G7 server, a four-node cc-NUMA system with four Intel Xeon E7-4870 2.4 GHz CPUs (80 logical processors) and 512 GB of DDR3 REG RAM across 32 modules. The system runs SUSE Linux Enterprise Server 15 SP4 with kernel version 5.14.21-150400.24.41.

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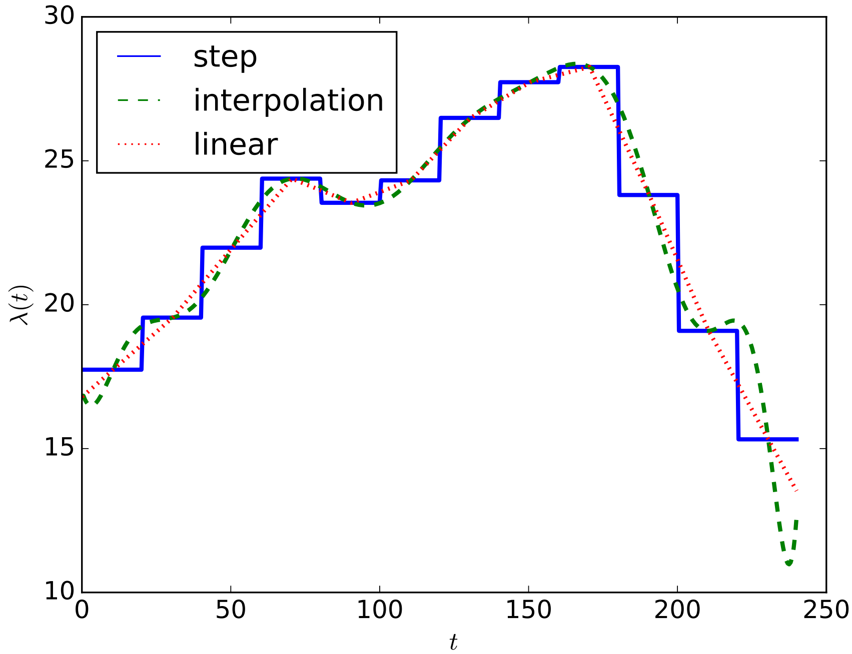

Fig. 1. Dynamic evolution of the mean arrival rate of EVs to the charging station, $\lambda(t)$ from 9:00 to 20:00.

3 Performance evaluation and operational optimisation of the fast charging station

We evaluate the impact of charging station management policies on the performance of the charging station. The performance metrics considered in this study is the mean number of EVs present at the charging at time t denoted as $E[N(t)]$. It is derived using the probability density function of the diffusion process as determined in the previous section

$$E[N(t)] = \int_0^N x f(x, t; \psi) dx. \tag{4}$$

The EV charging time depends on battery capacity, initial and target states of charge (SoC_i and SoC_f), and charging power, P_c (in KW). It is given by:

$$T_c = (SoC_f - SoC_i) \frac{B}{P_c} \tag{5}$$

where $B = Q \cdot V$ is the battery's energy capacity, with Q as nominal capacity (Ah) and V as voltage (V).

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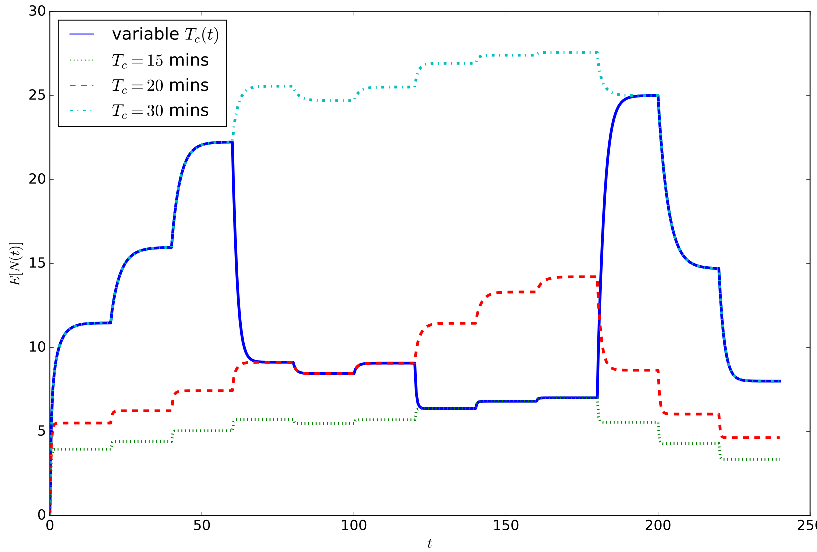

Fig. 2. The influence of dynamic changes of mean charging times $T_c(t)$ (by adjusting the final state of charge at time t denoted as $SoC_f(t)$) on the transient evolution of the mean number of EVs, $E[N(t)]$ from 9:00 to 20:00.

The performance of charging stations mainly depends on the customer arrival rate, λ, and the charging duration, $T_c = 1/\mu$. Arrival rate values used in the simulations are taken from [12]. Figure 1 shows the interpolated hourly mean arrival rate, $\lambda(t)$, from 9:00 to 20:00, based on Tables 1 and 2. All figures use a 6-minute time unit, covering 11 hours (220 intervals).

To remain consistent with the dataset in [12], we assume a Poisson arrival process, although the diffusion approximation supports general arrival patterns. Accordingly, the squared coefficients of variation are set to $C_A^2 = C_B^2 = 1$. The system is configured with a maximum parking capacity of $N = 30$, a waiting area for up to $K = 20$ vehicles, and each EV has a battery capacity of $B = 50$ kWh. The charging power is set to $P_c = 50$ kW, identical across all ports, implying uniform charging durations T_c or equivalently, a consistent charging rate μ across all ports.

To evaluate the impact of charging duration and queue management strategies, we vary the final state of charge (SoC_f) of arriving vehicles. Each EV is assumed to arrive with an initial state of charge $SoC_i = 20\%$, and all vehicles have a battery capacity of $B = 50$ kWh. Adjusting SoC_f directly affects the

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Table 1. Data for Scenario 1 ($c = 10$, SoC_f in %, and $T_c(t)$ in mins

t	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00
$\lambda(t)$	17.74	19.55	21.98	24.38	23.54	24.32	26.49	27.73	28.26	23.81	19.09	15.32
SoC_f	70	70	70	53	53	53	45	45	45	70	70	70
$T_c(t)$	30.00	30.00	30.00	20.00	20.00	20.00	15.00	15.00	15.00	30.00	30.00	30.00
$\mu(t)$	2.00	2.00	2.00	3.00	3.00	3.00	4.00	4.00	4.00	2.00	2.00	2.00

Table 2. Data for Scenario 2 ($T_c = 30.00$ minutes or $\mu = 2.00$)

t	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00
$\lambda(t)$	17.74	19.55	21.98	24.38	23.54	24.32	26.49	27.73	28.26	23.81	19.09	15.32
$c(t)$	10	10	10	13	13	13	15	15	15	10	10	10

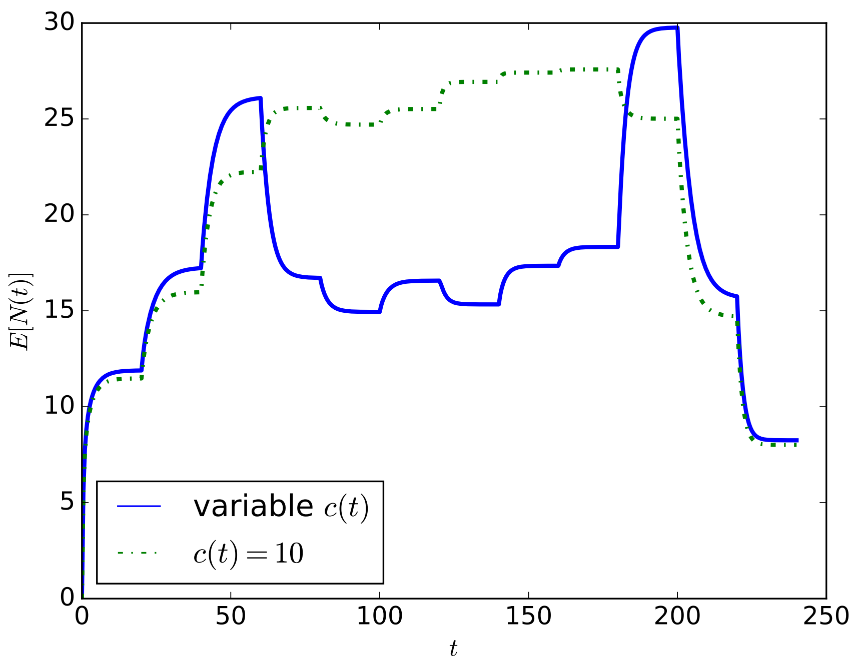

Fig. 3. The influence of dynamic changes of number of charging ports at time t denoted as $c(t)$ on the transient evolution of the mean number of EVs, $E[N(t)]$ from 9:00 to 20:00.

charging duration. For example, charging up to $SoC_f = 70\%$ yields a charging time $T_c = 30$ minutes, based on Equation 5.

Figures 2 and 3 illustrate two operational optimisation strategies and their effects on the transient queue size at the charging station.

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In the first scenario (Fig. 2), T_c or the service rate μ is reduced during peak hours by capping SoC_f, as shown in Table 1. Lowering SoC_f shortens T_c, reducing congestion. We also compare limiting SoC_f only during peak hours with applying it throughout the day. For instance,

$$SoC_f = \{45, 53, 70\}, \quad T_c = \{15, 20, 25, 30\} \text{ minutes},$$

show how more aggressive restrictions (e.g., $SoC_f = 45\%$, $T_c = 15$ min) significantly reduce queue size but may lower user satisfaction, as most drivers prefer to charge up to at least 80%. Hence, increasing charging power or the number of ports may be more acceptable alternatives.

In the second scenario (Fig. 3), the number of active charging ports is increased during peak demand (12:00–17:00). Once demand drops and grid load increases after 17:00, ports are scaled down. This strategy enhances queue management and aligns with grid efficiency goals.

4 Conclusion

The increasing adoption of electric vehicles (EVs) necessitates the development of efficient charging infrastructure to accommodate rising demand while minimizing congestion and service delays. In this study, we proposed a G/G/c/N diffusion-based queueing model to evaluate the performance of EV charging stations under time-varying arrival rates. Unlike traditional M/M/c models, our approach accounts for general arrival and service time distributions, providing a more realistic representation of charging station dynamics.

Our analysis revealed that queue lengths and waiting times fluctuate based on EV arrival patterns, with peak congestion occurring during high-demand hours. By examining the effects of different charging durations, we demonstrated that imposing a final state of charge (SoC_f) threshold significantly improves station efficiency. Specifically, limiting SoC_f reduces charging times, increases throughput, and lowers the number of lost customers who are unable to charge due to full station capacity. These findings highlight the critical role of queue management strategies in optimizing charging station performance. Future research can extend this work by incorporating more complex traffic patterns, multiple classes of customers and charging ports, and dynamic pricing strategies to further improve the efficiency of EV charging infrastructure.

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