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Analyzing Coincident Factors of Public Electric Vehicles in Ho Chi Minh City: A Monte Carlo Approach

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ABSTRACT

This study presents the method of calculating the coincident factor (CF) for public electric vehicles (PEVs) using Monte Carlo Simulation (MCS). The paper focuses on predicting future charging demand for electric buses (EBs) and electric taxis (ETs) in the greater Ho Chi Minh City (HCMC) metropolitan area, which, since July 1, 2025, has officially expanded to include Binh Duong and Ba Ria–Vung Tau provinces. The projection is based on population growth and public electric vehicle (PEV) penetration scenarios. It builds three scenarios for the years 2030, 2035, and 2040 to estimate the number of PEVs and their charging behaviours. The simulation runs 1,000 times for each vehicle type and scenario to calculate the CF. Results show that while the total number of PEVs increases over time, the CF slightly decreases, indicating that charging loads become more distributed across the day. For example, the CF for ETs changes from 0.26 in 2030 to 0.24 in 2040, while for EBs it stays around 0.35. These findings highlight the need for better charging management strategies and infrastructure planning to reduce grid overload risks and improve power system stability, especially for the newly enlarged urban area.

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1. Introduction

The global transition toward PEVs is becoming an essential pillar of sustainable urban development, particularly in rapidly growing metropolitan regions. In this context, EBs and ETs are emerging as the two most prominent forms of zero-emission public transport [1]. While EBs provide scheduled mass transit services along fixed routes, ETs serve as flexible, on-demand transportation options that complement fixed-line systems. Together, they form the backbone of next-generation public mobility ecosystems in cities aiming for decarbonization and smart infrastructure integration [2].

Vietnam is no exception to this trend. Recent policy shifts and private-sector investments have accelerated the deployment of PEVs, especially in the greater HCMC metropolitan area, which now encompasses the neighbouring provinces of Binh Duong and Ba Ria–Vung Tau [3]. This expanded urban zone is the most populous and economically dynamic region in Vietnam, with a growing reliance on high-frequency transport services to serve its residents, commuters, and tourists. Since 2021, the city has piloted electric bus fleets on key urban corridors, while electric taxi services, most notably operated by Green SM (a subsidiary of VinFast), have gained substantial market share, particularly around airports, business centers, and residential zones [4]. These developments reflect a broader national vision for sustainable transportation, as outlined in Vietnam's Green Energy Transition Program [5].

Despite the environmental and social benefits, the rapid adoption of PEVs also presents significant challenges, chief among them being the pressure on the urban power grid caused by simultaneous charging demand [6]. Both EBs and ETs exhibit relatively predictable but concentrated charging behaviours: buses often require two charging sessions per day (midday and overnight), while taxis, despite their operational flexibility, tend to cluster charging events during shift changes or at centralized charging hubs [7]. If a large number of these vehicles initiate charging within the same time frame, it can result in peak load congestion, voltage fluctuations, and grid instability, particularly in areas where charging infrastructure is still under development [8].

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To assess and manage this issue, researchers use a key indicator known as the CF, which quantifies the proportion of PEVs charging concurrently at any given time. A high CF indicates tightly clustered charging behaviour, which increases the risk of grid overload, whereas a lower CF implies a more balanced load distribution and more efficient use of charging infrastructure [9].

In the existing body of research, MCS is widely employed to model PEV charging patterns due to its ability to incorporate uncertainty and randomness in user behaviour. MCS has been particularly effective in modelling residential and commercial PEV fleets, where stochastic variability plays a significant role [10]. However, public transport systems – especially EBs and ETs – are characterized by more structured operational schedules. In such cases, the assumptions of randomness in MCS may not fully capture real-world charging behaviour [11]. Alternative modelling techniques, such as time-based probability distributions, Markov chains, or agent-based modelling, have been explored in limited studies to reflect the semi-deterministic nature of PEVs' operations [12] - [14].

Nonetheless, there remains a critical research gap in modelling and analyzing the CF of PEV fleets in Southeast Asian megacities, where urban morphology, traffic density, and service frequency differ significantly from Western contexts. Furthermore, few studies have simultaneously examined both EBs and ETs as coexisting elements of the public transport system [15], [16].

This study aims to address this gap by focusing on the charging behaviour and CF analysis of EBs and ETs operating within the expanded HCMC metropolitan region. It develops three future scenarios 2030, 2035, and 2040 based on expected fleet growth and policy targets, and simulates daily charging loads using realistic operational assumptions for both vehicle types. The key objectives are to estimate CF under each scenario, identify critical time windows of high charging overlap, and propose recommendations for grid management and charging station deployment.

By narrowing the study scope to two major PEV modes and applying it to Vietnam's largest urban corridor, the research offers practical insights for urban planners, electricity authorities, and mobility operators. These insights will support the development of smart, resilient infrastructure systems capable of accommodating the accelerating shift toward clean, electrified public mobility.

2. Methodology

2.1. Define Scenarios

To assess future charging demand and infrastructure pressure, three scenarios are defined based on national and regional transportation electrification goals [17]:

Scenario 1 (2030): Initial stage of PEV adoption.

Scenario 2 (2035): Mid-level electrification under policy acceleration.

Scenario 3 (2040): Full transition to PEVs.

Each scenario includes estimated values for population size, fleet size (buses and taxis), and PEV penetration rates, serving as inputs for simulation.

2.2. Mathematical Model

2.2.1. Linear Regression (LR)

To estimate the future population based on past data, we use a simple LR method. This method finds the straight-line relationship between the year (independent variable) and the population (dependent variable). The formula is explained as follows [18]:

$$\hat{y} = \left(\frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n} (x_i - \overline{x})^2} \right) (x - \overline{x}) + \overline{y} \tag{1}$$

Where, $\hat{y}$ is the estimated population for year x; x_i, y_i are the actual values for year i and its population; $\overline{x}$, $\overline{y}$ are the average values of the dataset for x_i and y_i, n is the number of years used for the calculation.

2.2.2. Compound Exponential Function (CEF)

To predict the number of vehicles in the future, we need to use the yearly growth rate of this factor. The formula is given below [19]:

$$F(n) = F_0.(1+r)^{n-t_0} \tag{2}$$

Where, F_0 is the starting value at the first year t_0; $F(n)$ is the vehicle rate in year n; r is the yearly growth rate; and $n-t_0$ is the number of years counted from the starting year t_0.

2.2.3. Binomial Distribution Model (BDM)

To simulate the chance that an action happens at the same time, we use the BDM [20]. Let the random variable $X \sim Bin(n,p)$ represent the number of successes in n independent trials, with the success chance for each trial being p. Then, the probability of getting exactly k successes are given by:

$$\mathbb{P}(X=k) = \binom{n}{k} p^k (1-p)^{n-k} \tag{3}$$

Where, p is the chance of success in one trial; $1-p$ is the chance of failure; $\mathbb{P}(X=k)$ is the probability that exactly k vehicles will do the charging action; and the combination number for choosing k from n is explained by the following formula:

$$C_n^k = \binom{n}{k} = \frac{n!}{k!(n-k)!} \tag{4}$$

2.2.4. Cumulative Distribution Function (CDF)

The main points of the CDF are as follows [21]:

$$F(k) = \mathbb{P}(X \le k) = \sum_{i=0}^{k} \binom{n}{i} p^i.(1-p)^{n-i} \tag{5}$$

Where, the CDF $F(k)$ is the total chance of having at most k successes in trials. Here, $k \in \{0,1,\ldots,n\}$ is the threshold level. If we want to find the smallest k where the cumulative chance is greater than or equal to a given value $\alpha \in (0,1)$, we use this:

$$k^* = \min\{k \in \mathbb{N} : F(k) \ge \alpha\} \tag{6}$$

2.2.5. Coincident Factors (CFs)

To measure how many vehicles charge at the same time, the process has two steps [22]: First, calculate the average number of vehicles charging during each time slot in a day; Second, calculate the CF for each vehicle type.

$$CF_v = \bar{C}_v / N_v \tag{7}$$

Where, CF_v is the coincident factor for electric vehicles; $\bar{C}_v$ is the average number of vehicles charging in one hour, calculated over all 24 hours in a day; N_v is the total number of vehicles of type v in the scenario; the value of $\bar{C}_v$ is calculated as follows:

$$\bar{C}_v = \frac{1}{24}\sum_{h=1}^{24}\bar{C}_{v,h} \tag{8}$$

Where, $\bar{C}_{v,h}$ is the average number of vehicles of type v charging at an hour h calculated as:

$$\bar{C}_{v,h} = \frac{1}{S}\sum_{s=1}^{S} C_{v,h}^{(s)} \tag{9}$$

Where, $C_{v,h}^{(s)}$ is the number of vehicles charging at hour h during the simulation run s; S is the total number of simulation runs.

To provide a comprehensive view of the simulation process, the overall modeling framework is summarized in Figure 1. It outlines the sequential steps from historical data input and forecasting to the estimation of CFs using MCS.

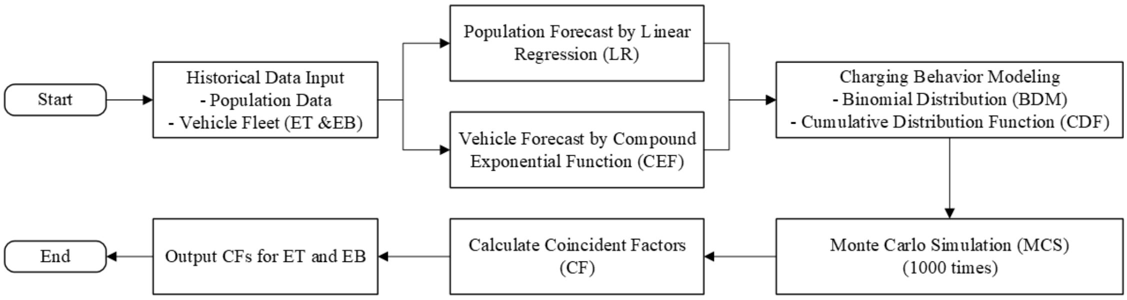


Figure 1. *Simulation flowchart for estimating CFs of PEVs using MCS*

3. Calculation and Simulation

3.1. Case study

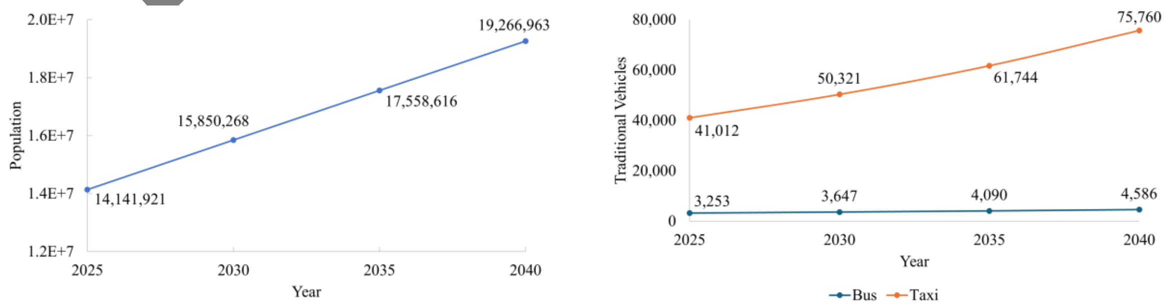
3.1.1. Population

Population data for HCMC, Binh Duong Province, and Ba Ria – Vung Tau Province in the years 2022, 2023, and 2024 were collected [23]. Formula (1) was used to calculate the linear population growth. Based on this, the future population after the merger until the year 2040 was predicted. The calculation results are shown in Table 1 and illustrated in Figure 1.

Table 1. *Population forecast to 2040 (people)*

Year	2025	2030	2035	2040
Population	14,141,921	15,850,268	17,558,616	19,266,963

3.1.2. Traditional Vehicles (TVs)



(a) *(b)*

Figure 2. *Forecast chart until 2040: (a) Population (people); (b) Traditional Vehicle (units)*

There are 0.23 buses for every 1,000 people, with an average yearly growth rate of 12.13% [24]. For taxis, the current number is 0.29 taxis for every 100 people, and the average yearly growth rate is 22.70% [25]. Formula (2) is used to predict the future growth of both types of vehicles. The results are shown in Table 2 and illustrated in Figure 2.

Table 2. *Total number of TVs (units)*

Year	2025	2030	2035	2040
Taxi	41,011	45,965	50,920	55,874
Bus	3,252	3,645	4,038	4,431

3.2. Estimation of CFs by MCS

3.2.1. Monte Carlo Simulation (MCS)

MCS is a computational approach that uses random sampling techniques and probability theory to describe systems influenced by uncertain or variable factors. This method helps in evaluating risks, analyzing uncertainties, and predicting possible outcomes in complex scenarios [26].

In this paper, MCS is used to simulate random charging behaviors of different PEV categories. Applying stochastic probability distributions that reflect actual charging patterns, and using mathematical expressions (3), (4), (5), and (6), the study calculates the probability of multiple vehicles charging at the same time.

3.2.2. Scenarios Development

According to Decision No. 876/QD-TTg dated July 22, 2022, the Deputy Prime Minister approved the Action Program for Green Energy Transition and for reducing carbon dioxide and methane emissions in the transport sector [27]. In alignment with this policy, a set of penetration scenarios for plug-in electric vehicles (PEVs) has been developed, targeting two primary vehicle types: electric taxis and electric buses. Table 3 presents both the penetration rates (%) and the corresponding number of electric vehicles (units) for each vehicle type across three defined scenarios for the years 2030, 2035, and 2040.

Table 3. *Penetration scenarios and vehicle quantities for Electric Taxis and Buses (units)*

Scenario	Scenario 1 (2030)		Scenario 2 (2035)		Scenario 3 (2040)	
Electric Taxis	50%	22,982	75%	38,190	100%	55,874
Electric Buses	70%	2,551	85%	3,432	100%	4,431

3.2.3. Charging behavior of different types of EVs

To design a suitable charging infrastructure, it is important to understand the typical charging methods and charging behaviours of different types of EVs, especially PEVs such as EBs and ETs [28].

Electric bus (EB): This type of bus usually runs the same distance every day, about 70 km. To make sure it works safely, it needs to charge two times a day. Normally, EBs use fast charging at lunchtime and slow charging at night after work. The charging happens from 9:30 am to 4:00 pm and from 11:00 pm to 5:00 am the next day.

Electric taxi (ET): This type of taxi works from 6:00 am to midnight. Each day, it travels about 400 km. ETs need to be charged twice a day. Drivers usually choose to charge at noon and in the evening. Because they have little rest time, they often use fast charging to save time. The charging times for taxis are from 2:00 am to 5:00 am and from 11:30 am to 2:30 pm.

Figure 3 shows the typical charging time for both buses and taxis over 24 hours. As shown, taxis and buses have different charging patterns due to their daily operating schedules.

Although EBs follow fixed operational routes, their actual charging behaviours may still exhibit stochastic characteristics. In dense urban environments such as Ho Chi Minh City, real-world uncertainties – including traffic congestion, queuing delays at charging hubs, or driver-specific adjustments – can lead to variability in the timing and overlap of charging sessions. For this reason, the

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use of MCS remains appropriate, as it allows for the incorporation of these random fluctuations in estimating the CF of charging events across the fleet.

Additionally, the probability p of vehicles charging at each hour of the day is provided in Table 4(a) and Table 4(b). This value reflects the chance that each type of PEV is charging during any given hour within 24 hours.

Table 4 (a). *Hourly probability distribution p of PEV usage (Hour 1-12)*

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
ET	0.2	0.3	0.4	0.5	0.5	0.2	0.05	0.05	0.05	0.1	0.2	0.3
EB	1	1	1	1	1	0.01	0.01	0.01	0.2	0.2	0.1	0.2

Table 4 (b). *Hourly probability distribution p of PEV usage (Hours 13–24)*

Hour	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
ET	0.5	0.5	0.4	0.1	0.05	0.05	0.1	0.2	0.2	0.3	0.3	0.4
EB	0.1	0.2	0.1	0.1	0.01	0.01	0.05	0.05	0.05	0.05	1	1

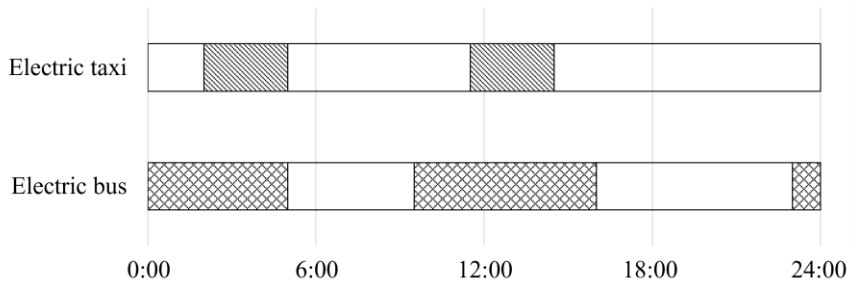


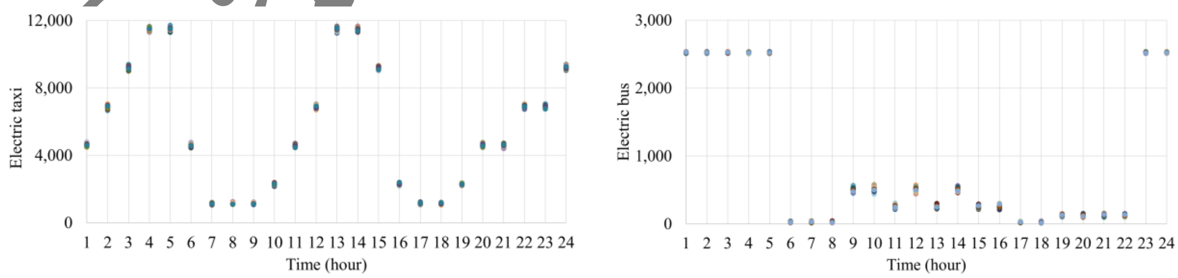
Figure 3. *Charging behaviors of PEVs*

4. Results and Discussion

4.1. Results

4.1.1. Low-level scenario – Scenario 1 (2030)

Using formulas (3), (4), (5), and (6), the simulation was run 1,000 times to predict the number of ETs and EBs charging at each hour in 2030.



(a) *(b)*

Figure 4. *Hourly charging of PEVs after 1,000 simulations – Scenario 1 (2030): (a) ET; (b) EB (units)*

Figure 4(a) shows the number of ETs charging during each hour of the day. The highest number is about 12,000 units, happening mostly between 4:00–5:00 am and 1:00–2:00 pm. The lowest number is around 600 units, appearing late at night.

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Figure 4(b) shows the number of EBs charging during each hour. Most charging happens at night, especially after 11:00 pm, with nearly 100% of the buses needing to be charged during this time. The number ranges from around 300 units at the lowest to over 2,500 units at the highest.

The summary of the highest number of vehicles charging at any hour after 1,000 simulation runs for this scenario is shown in Table 5.

Using formulas (7), (8), and (9), the average number of vehicles charged and the CF for each type of PEV in the low-level scenario – Scenario 1 (2030) are calculated and presented in Table 5.

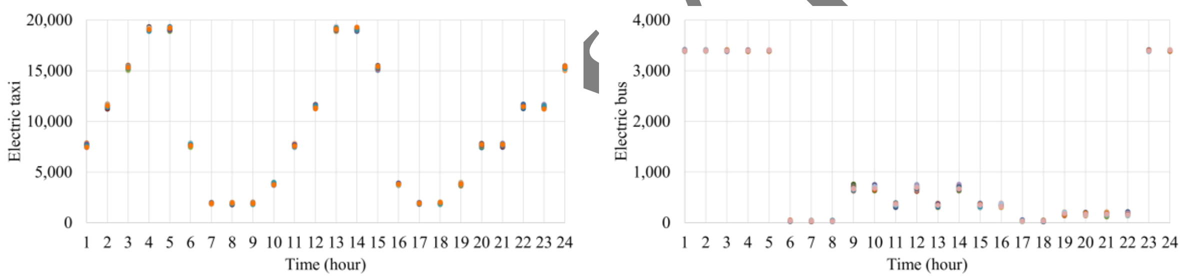
Table 5. *Average number of vehicles charged and coincident factors – Scenario 1 (2030)*

Transportation	$\bar{C}_v$	CF
Electric Taxi	5,881	0.26
Electric Bus	925	0.36

4.1.2. Medium-level scenario – Scenario 2 (2035)

Similar to Scenario 1 (2030), Figure 5(a) shows that the highest number of ETs needing to be charged is over 18,000 units, while the lowest is around 2,000 units.

Figure 5(b) shows the number of EBs needing charging over 24 hours, with most charging occurring at night after 23:00. The highest number reaches over 3,000 units.



(a) (b)

Figure 5. *Hourly charging of PEVs after 1,000 simulations – Scenario 2 (2035): (a) ET; (b) EB (units)*

The calculation of the average number of vehicles charging per hour and the CF for each type of PEV under the medium-level scenario – Scenario 2 (2035) has been completed. The results are summarized in Table 6.

Table 6. *Average number of vehicles charged and coincident factors – Scenario 2 (2035)*

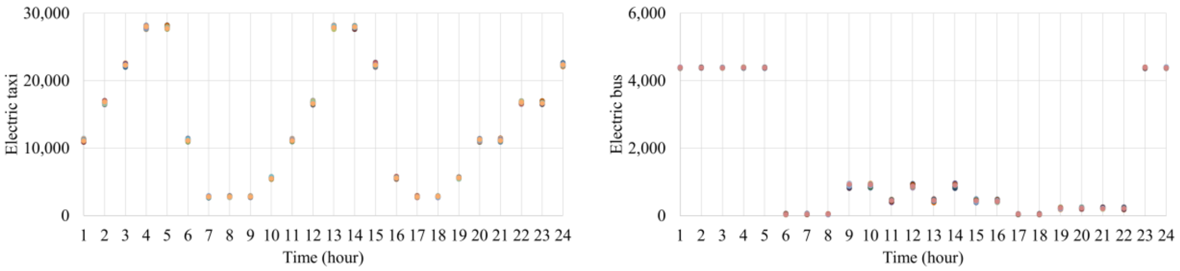
Transportation	$\bar{C}_v$	CF
Electric Taxi	9,700	0.25
Electric Bus	1,239	0.36

4.1.3. High-level scenario – Scenario 3 (2040)

Similar to the scenario 1 (2030), and scenario 2 (2035) presented earlier, Figure 6(a) shows the number of ETs needing charging over 24 hours, with the highest number around 28,000 units, mostly between 4:00–5:00 and 13:00–14:00, and the lowest at about 2,000 units.

Figure 6(b) shows the number of EBs needing charging over 24 hours, with most charging occurring at night after 23:00. The highest number reaches over 4,000 units.

The calculation of the average number of vehicles charging per hour and the CF for each type of EV under the high-level scenario – Scenario 3 (2040) has been completed. The results are summarized in Table 7.



(a) *(b)*

Figure 6. *Hourly charging of PEVs after 1,000 simulations – Scenario 3 (2040): (a) ET; (b) EB (units)*

Table 7. *Average number of vehicles charged and coincident factors – Scenario 3 (2040)*

Transportation	$\bar{C}_v$	CF
Electric Taxi	14,123	0.24
Electric Bus	1,591	0.35

4.2. Discussion

The simulation results show that the CF for ETs decreases from 0.26 in 2030 to 0.24 in 2040, while the CF for EBs remains steady around 0.35 in Figure 7. This trend reflects the faster fleet growth and more diverse charging behaviours of ETs, compared to the slower expansion and fixed schedules of EBs. As charging becomes more distributed over time, overall stress on the grid may be reduced. However, concentrated peak periods such as late night for buses and midday for taxis still require targeted planning.

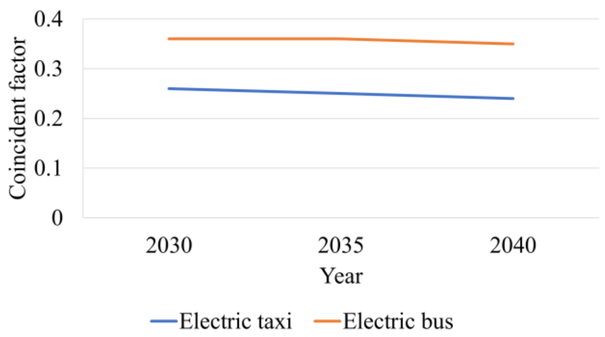


Figure 7. *CF curves for three scenarios using the MCS approach*

While CF serves as a useful metric of simultaneous charging, this study does not directly assess its implications on grid-level indicators such as hourly demand peaks, voltage deviations, or asset loading. Future research should extend the CF framework to quantify these technical impacts, thereby enabling grid operators to develop more robust and adaptive infrastructure strategies.

Moreover, the current simulation assumes spatial uniformity in vehicle deployment and infrastructure access. In reality, Ho Chi Minh City exhibits significant spatial heterogeneity in grid capacity and urban density. Accounting for these spatial-temporal dynamics in future studies will improve modelling realism and planning precision.

5. Conclusion

This study provides important insights for planners and policymakers as they prepare for a future with more EVs. The results show that with more PEVs, charging becomes more balanced during the day, helping to reduce stress on the electricity grid. To support this growth, cities will need smart and flexible charging systems, more fast-charging points, and good planning. Future research should focus on real-time charging control and better use of renewable energy, to make sure the power supply stays strong and stable as PEV use increases in the greater Ho Chi Minh City area.

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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